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Departamento de Automática, Ingeniería Eléctrica y
Electrónica e Informática Industrial

Tesis Doctoral

**Study and Analysis of the Behavior of LFP and
NMC Electric Vehicle Batteries concerning their
Ageing and their Integration into the Power Grid**

Autor: **Jorge Nájera Álvarez**

Ingeniero Industrial por la Universidad Politécnica de Madrid

Directores: **Jaime Rodríguez Arribas**

Doctor Ingeniero Industrial por la Universidad Politécnica de Madrid

Rosa María de Castro Fernández

Doctor Ingeniero Industrial por la Universidad Politécnica de Madrid

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Rosa María de Castro Fernández

Tribunal nombrado por el Mgnfco. y Excmo. Sr. Rector de la Universidad Politécnica de Madrid, el día ____ de _____ de 2020.

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*A los/as que me quieren bien.
Nunca entendí mi suerte,
pero siempre celebré vuestro criterio.*

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Resumen y principales aportes

En esta tesis se analiza el envejecimiento de baterías de ion-litio desde dos puntos de vista: los sistemas híbridos de almacenamiento de energía y el desarrollo de modelos de envejecimiento. Por otra parte, se analiza la influencia de los controles de carga inteligentes de vehículos eléctricos en la red eléctrica.

En el ámbito de los sistemas híbridos de almacenamiento de energía, esta tesis estudia la hibridación de baterías de ion-litio con supercondensadores. A este respecto, se estudia y se propone una metodología de dimensionado para este tipo de sistemas, de forma que se optimice la vida útil de las baterías y la eficiencia energética del sistema. También se presenta un ejemplo de aplicación para un autobús eléctrico.

Dentro del desarrollo de modelos de envejecimiento para baterías de ion-litio, se desarrolla un modelo válido para las dos químicas más relevantes, LFP y NMC. Este modelo, que incluye tanto el envejecimiento de ciclado como el envejecimiento por el paso del tiempo, se valida teóricamente para ambas químicas, y se realiza una validación experimental parcial mediante ensayos de laboratorio.

Para estudiar la influencia de los controles de carga inteligentes de vehículos eléctricos en la red se han seleccionado controles que corrigen desequilibrios y niveles de tensión. Mediante modelos y simulaciones se ha estudiado la influencia de los controles en una red estándar de BT. También se ha desarrollado un estudio estocástico con métodos de Montecarlo para generalizar las conclusiones a diferentes tipos de redes de BT.

Las principales contribuciones de esta tesis se enumeran a continuación: desarrollo de un modelo de pérdida de capacidad on-line junto con una metodología de dimensionado para un sistema híbrido de baterías y supercondensadores; desarrollo y validación de un modelo de pérdida de capacidad válido para las químicas LFP y NMC dentro del ion-litio, incluyendo una metodología de parametrización de los modelos desarrollados; análisis de la influencia de controles de carga inteligente en los parámetros de red, y desarrollo de una estudio estocástico para generalizar las conclusiones.

Abstract and main contributions

In this thesis the Li-ion battery ageing is analyzed from two different perspectives: hybrid energy storage systems, and the development of capacity fade models. Moreover, the influence of electric vehicle smart charging controls in the power grid is assessed.

Regarding hybrid energy storage systems, this thesis analyzes the hybridization of Li-ion batteries with supercapacitors. In this regard, a dimensioning methodology is proposed for those systems, so the Li-ion batteries lifespan and the energy efficiency of the whole hybrid system are optimized. Besides, an application example for implementing the developed methodology is provided.

According to the capacity fade models for Li-ion batteries, a model valid for both LFP and NMC, the two most relevant chemistries among the Li-ion family, is developed. This model, which includes both calendar and cycling ageing, is theoretically validated for both chemistries, and a partial experimental validation is performed with laboratory tests.

In order to study the influence of smart charging controls for electric vehicles in the power grid, a set of controls that mitigate unbalance and correct voltage levels is selected. By using models and computer simulations, the influence of those controls on a LV power grid is analyzed. Moreover, a stochastic analysis based on Montecarlo simulations is performed, so conclusions can be generalized for other LV grid typologies.

The main contributions of this thesis are listed as follows: development of an on-line capacity fade model for Li-ion batteries, including a dimensioning methodology for a hybrid energy storage system with batteries and supercapacitors; development and validation of a capacity fade model valid for both LFP and NMC chemistries, including a parametrization methodology for the model; analysis of the influence of smart charging controls for electric vehicles in the grid parameters, and development of a stochastic analysis so conclusions can be generalized.

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1 | Introduction

Electric transports are, slowly but undoubtedly, becoming a real alternative to traditional combustion engine cars. In recent years, several European countries have set electric transport deployment targets as a key measure for reducing pollutant and greenhouse gas emissions, specifically in urban areas. Moreover, financial incentives, the increased availability of charging infrastructure, and certain benefits when accessing and parking in some urban areas in many European cities, are crucial factors for the expected growth of EV market shares during the next decade.

However, energy storage systems (ESSs) are still the bottleneck for electric transportation, and will keep being so for some time due to their relatively low energy density and ageing, which reduces the ESS lifespan increasing the yearly cost of the transport. Hence, the electrical storage technologies used in electric transports are one of the key issues to ensure this development due to their driving range, manufacturing costs, and ESS replacement needs. Lithium-ion (Li-ion) batteries are the most applicable technology nowadays, and it is expected to remain as the preferred ESS for the next decade.

Li-ion batteries suffer from degradation due to their usage and their exposure to environmental conditions. This degradation, commonly called ageing, affects both the ability of the battery to store energy, and its ability to deliver the power demanded by the load, diminishing both as the ageing increases. Since those two parameters severely limit the battery suitability for a specific application, it is demanded to have information about the evolution of those parameters at any point along its life. Moreover, different techniques can be applied to extend at maximum the lifespan of the Li-ion batteries, both under driving conditions or when connected to the electric power grid for charging purposes. In this thesis, focus was put on three aspects of the Li-ion battery ageing, aiming for a complete approach.

At first, a Li-ion battery ageing is analyzed together with a set of supercapacitors (SCs) in a hybrid ESS topology. The purpose of this hybrid ESS is to protect the battery from high charge/discharge currents. In this way, the SCs are controlled to deal with those high charge/discharge currents, which does not represent a problem for its lifespan

given its characteristics. Hence, the battery is forced to work with low current values and low temperatures, reducing the capacity fade and extending its life.

This first analysis was performed with a Li-ion battery with LFP chemistry. Given that the different chemistries among Li-ion family follow a dissimilar degradation process, the author aimed for developing a model which is valid not only for studying the ageing in a single Li-ion chemistry, but for the most relevant chemistries. Hence, a second analysis was performed for ageing models for Li-ion batteries. LFP and NMC chemistries were selected for developing a capacity fade model valid for both of them, given that their expected market share during the following decade is expected to be much higher than for the rest of chemistries.

At last, and given that electric transports (specifically electric vehicles) are expected to be connected during long periods of time at LV distribution grids causing load unbalance and extra power consumption, smart charging controls for reducing voltage unbalance and correcting voltage levels have been analyzed. The influence of the selected smart charging controls has been analyzed both from the point of the benefits provided to the power grid.

Hence, the followed approach is focused on studying the Li-ion battery ageing from two different perspectives: the hybridization with SCs, the capacity fade modelling for NMC and LFP chemistries. Besides, the influence of smart charging controls in the power grid parameters is analyzed.

2 | Hybrid Energy Storage Systems Dimensioning for Electric Trans- ports

2.1 Introduction

This chapter studies the Li-ion battery ageing by focusing on the energy storage system (EES) of electric transports. Specifically, this chapter analyzes the dimensioning process of hybrid energy storage systems (HESSs) comprised of electric batteries and supercapacitors (SCs), regarding the energy efficiency and battery ageing. The analyzed system includes the following elements: a battery pack formed by lithium-ion (Li-ion) batteries, a SCs pack formed by electrostatic double-layer capacitors (EDLCs), a DC-DC converter, and a load representing the electric transport fed by the HESS.

The objectives of this part of the dissertation are the following:

- Develop an on-line ageing model estimation for Li-ion batteries, so the battery model performance is influenced by the capacity loss.
- Develop a HESS dimensioning methodology, taking into consideration the control strategy and the driving cycle for a chosen HESS topology.
- Perform an application example to assess the performance of the whole HESS in terms of power losses, runtime (driving range), and battery ageing for two different driving cycles for an electric bus.

There are three publications derived from this chapter:

- Journal: J. Nájera, P. Moreno-Torres, M. Lafoz, R. de Castro and J. R. Arribas, "Approach to Hybrid Energy Storage Systems Dimensioning for Urban Electric Buses Regarding Efficiency and Battery Ageing," *Energies*, vol. 10, no. 11, p. 1708, 2017.

- Conference: J. Nájera, J. R. Arribas, R. M. de Castro, "Hybridization percentage influence on Hybrid Energy Storage Systems efficiency for Electric Buses," in *Industriales Research Meeting 2017 (IRM17)*, Madrid, Spain, 2017.
- Conference: P. Moreno-Torres, J. Nájera, M. Yeguas, J. R. Arribas, M. Lafoz, "Hybrid Energy Storage Systems for Electric Vehicles: Influence of typology and hybridization percentage on efficiency," in *First Symposium Segvauto-Tries-CM*, Madrid, Spain, 2016.

2.2 HESSs for electric transports

2.2.1 Overview of ESSs for electric transports

The huge impact that transportation has on greenhouse gas emissions is well known. According to the US Environmental Protection Agency (EPA), around 26% of the total greenhouse gas emissions are caused by transports, and, from that percentage, 22% corresponds to heavy vehicles like buses and freight trucks [45]. Transport electrification policies have been applied, for instance, by the European Union, with the objective of reducing transportation emissions, and, in fact, this is one of the key research areas of the Horizon2020 European research programme [89]. Additionally, there are multiple European cities that are restricting the access of combustion engine vehicles to urban areas [65], which makes it even more crucial to electrify urban transportation in order to have livable and sustainable cities.

Energy storage systems (ESSs) are still the bottleneck for electric transportation and will keep being so for some time due to their low energy density and high cost (Figure 2.1). The electrical storage technologies used in Electric Vehicles (EVs) and Electric Buses (EB) are one of the key issues to ensure this development due to their driving range and manufacturing costs [93, 76]. Only a few technologies are applicable nowadays, namely batteries, hydrogen fuel cells, and EDLCs.

EDLCs are high power density storage systems, while batteries and fuel cells compete against each other as they are both high energy density storage systems. At present, batteries are ahead in terms of Technology Readiness Level, Regulatory Readiness Level, and Customer Readiness Level [93, 76, 124]. Research on new battery chemistries such as lithium-metal, lithium-sulfur, or metal-air is promising and maybe optimistic as well (Figure 2.2). However, batteries are not exempt from drawbacks such as those related to thermal behavior and ageing, derived from the demanding power profile and the number of cycles required, which will strongly affect their life.

Figure 2.1 Ragone chart comparing different ESS.

Figure 2.2 Established and emerging battery technologies comparison.

Given that batteries and EDLCs provide complementary capabilities, the use of a combined solution of both technologies, known as a Hybrid Energy Storage System (HESS), seems to provide clear advantages. The synergy of using a combination of batteries and EDLCs provides potential for achieving better performance at the cost of higher complexity. This extra expertise requirement is probably one of the reasons why current commercial hybrid and electric transports still use either batteries or EDLCs as electrical ESS, although future electric vehicles and buses may evolve towards HESS, consisting of batteries and EDLCs together.

There are already many studies in the scientific literature that approach the topic of HESS for electrical transports from the topology, from the dimensioning, or from the

Table 2.1 HESS boost topologies selected.

Topology	Controlled variables	Schematic
1: Two-stage batteries-EDLCs	I_{BAT}
2: Two-stage EDLCs-batteries	I_{EDLC}
3: Parallel active	$U_{DC}/I_{BAT}/I_{EDLC}$

control strategy point of view (e.g., [94, 26]). However, there are not many works that consider two or more aspects simultaneously. A complete evaluation of the benefits, considering all parts of the equipment, is likely to reveal that the total efficiency during the life cycle of the electric transport can be increased, while preserving the battery life.

2.2.2 HESS topologies

HESS for EVs and EB comprise two power sources (batteries and EDLCs) and one bidirectional load (the traction drive composed by the inverter, the traction motor, and the mechanical load). Using a combination of batteries and EDLCs, operating at different voltage allows the specific power and energy to be improved for each application since energy is mainly given by batteries and power is given by both batteries and EDLCs [82]. For such configuration, there are seven possible power topologies, consisting in a combination of batteries, EDLCs, and one or two power converters [76, 93, 82].

Control capabilities of those seven topologies are different among them. Therefore, some topologies have little room for optimization, while others can be properly controlled to get the most out of them. Among those seven topologies, only the three represented in Table 2.1 have been taken into consideration since they provide the minimum control flexibility required and increase the reliability during their implementation in an electric transport [76, 82]. All power converters are bidirectional.

In topology 1, “two-stage battery/EDLCs”, the DC-DC keeps batteries under control, which is preferable to the EDLCs as the former are more sensitive to extreme operation (high current, overdischarge, etc.). However, this advantage comes at the expense of the

under-use of the EDLCs, as their voltage will most likely be constrained within a narrow range and the capability of the EDLCs to provide/absorb power peaks is reduced, which, in turn, places more demanding operating conditions on the batteries. The DC-DC converter must keep the DC-link voltage U_{DC} (which is also the EDLCs voltage) within a certain range by charging and discharging the batteries. This control should allow U_{DC} to vary within a certain range so that the EDLCs are used as effectively as possible [26]. For example, a time-averaged load current is used as a current reference for the batteries in [54].

Topology 2, “two-stage EDLCs/battery”, is probably the most studied one. The EDLCs voltage may vary in a wide range (usually from 40% to 50% to 100%, which implies using around 75% of their storage capacity). In addition, their rated voltage may be lower when compared to the previous topology. However, the converter needs to be of higher power than the one in topology 1 since, the lower the EDLC voltage, the current demanded will be higher if a constant power supply is requested. Another limitation of this alternative is that the DC-link voltage U_{DC} cannot be varied as it is imposed by the battery pack [26]. The simplest way to control the system consists in rule-based strategies that cannot perform optimally [27, 6]. Particularly interesting is the work presented in [81], in which three rule-based control strategies are tested with three different goals: optimal power split between the batteries and the EDLCs, loss minimization, and State of Charge (SoC) optimization. The study suggests that even a simple control strategy enables efficient energy savings (when compared to conventional non-hybrid ESSs), but the author of the present work think that such a statement cannot be generalized, as is discussed later.

Topology 3, “parallel active”, has been receiving a lot of focus lately since it is arguably the most flexible topology for EBs applications. Indeed, it has flexible operating voltages and provides explicit power sharing control [76, 124, 93, 82], although both currents are not independent since, when either I_{BAT} or I_{EDLC} is prioritized for control, the other one is set by the traction drive. There is no doubt that it is the only topology with inherent redundancy since the failure of one source does not prevent the operation of the other, which, in some applications, is an important specification. For the reasons stated above, this alternative is preferred in traction applications. However some authors argue against this topology due to the weight of two power converters [81] and the extra cost.

Each of the three possible topologies presents advantages and disadvantages in terms of voltage flexibility, control flexibility, control complexity, effective capacity utilization, the number and size of the DC-DC converters (including weight, volume, and cost), and system reliability and redundancy. Topology 1 has the simplest control, where the power

converter controls the U_{DC} . Even though it is equipped with EDLCs and batteries, the truth is that it has only one ESS, since the SCs behave as an improved DC link. In this topology, the energy stored in the SCs cannot be used freely, and U_{DC} must be kept within a range, depending on the power converter. This means that much of the SCs energy is wasted, since it cannot be used. Topology 2 allows for more control possibilities than Topology 1, since the power converter does not have to control U_{DC} , which is imposed by the battery. Hence, there is no a predefined way to control the system, as it will be discussed in section 2.3.5. For the analysis carried out in Section 2.4, topology 2 has been chosen for the advantage of the combined storage technologies. Topology 1 was discarded since it has only one true ESS, as the EDLCs behave like an improved DC-link, and Topology 3 was discarded for weight, cost, and excessive complexity reasons.

2.3 HESS modelling

This section describes the different models used in section 2.5 for the application example. Four main elements are considered: a battery pack formed by Li-ion batteries, a SCs pack formed by EDLCs, a DC-DC converter, and a load representing the electric transport.

Regarding batteries and SCs, there is a wide variety of model topologies in the literature, which can be grouped into three main categories depending on the modelling approach [50, 163]: electrochemical models, intelligent or mathematical models, and equivalent circuit models.

Electrochemical models account for high accuracy and low calculation efficiency, and can provide full information about the dynamics of the ESS. However, these models capture the reactions inside the ESS by means of coupled partial differential equations (PDEs), which demand a considerably high computational effort when performing long term studies. Moreover, those PDEs equations require specific data for their parametrization, which is not commonly provided by manufacturers. Among the electrochemical models, the Li-ion battery models developed by Amiribavandpour et al., Smith et al., and Cai and White, and the SCs three-dimensional models developed by Allu et al. and Wan and Pilon are the most relevant [5, 22, 136, 3, 151].

Intelligent modelling techniques are associated with stochastic models, mostly developed with artificial neural networks or fuzzy logic. These models aim for depicting the nonlinear relationship between the ESS performance and its influencing factors, without a detailed understanding of the reactions inside the ESS. Nevertheless, these models require a large amount of training data in order to be accurate, and are commonly trained for a specific battery, making them non generalizable. The Li-ion battery model developed by

Rao et al., and the SCs models developed by Wu et al. and Eddahech et al. are the most relevant [117, 157, 44].

Equivalent circuit models imitate the dynamics of a ESS with a set of capacitors, inductances and resistances. They aim for simplicity, since they substitute the PDEs with ordinary differential equations. This greatly reduces the computational effort, and facilitate their implementation. Their accuracy varies depending on the complexity (number of elements and configuration). Commonly, higher complexity implies higher accuracy, but at the cost of increasing the number of elements that require parametrization. The Li-ion battery models developed by Lam et al., Tremblay et al., and Chen and Rincón-Mora, and the SCs models developed by Zhang et al., and Bland are the most relevant [83, 145, 30, 162, 19]

This chapter aims to obtain general conclusions, as well as develop a general methodology for designing HESS systems for electric transports. Hence, an equivalent circuit model has been selected for both the SC and Li-ion battery model. This approach allows for a widely applicable model, with a lower number of parameters. The resulting HESS model is not the most accurate model, but it is able to reach sufficient precision while facilitating its implementation.

2.3.1 Li-ion battery model

The Li-ion battery model used in this work is a modification of the model developed by Moreno-Torres in [36], which is based in the dynamic model provided by MathWorks in the Simscape Electrical™ library of Simulink®. The model accounts for a high accuracy/complexity ratio. The main characteristics, as well as the contributions to the model, are described along this section.

Voltage/runtime model

The Li-ion battery model developed in [36] is based on the Shepherd model, which describes the electrochemical behavior in terms of voltage, current, internal resistance and State of Charge (SoC) [135]. This model was modified and experimentally validated later in [145, 144], using SoC as the only state variable. Although more accurate equivalent circuits have been proposed [30], the modified Shepherd model keeps the error between 1% and 5% and does not require testing the battery to obtain parameters (datasheet information suffices). Naturally, having a simple and generalizable model that can be parameterized without laboratory test, require sacrificing some battery phenomena, such as Peukert's effect (capacity variation with discharge rate).

Figure 2.3 Modified Shepherd model proposed in [145].

In this thesis, the battery model developed in [36] has been implemented, which has the same behavior than the modified Shepherd model for voltage/runtime purposes. The main modification, as shown in Fig.2.4, is the representation of the internal resistance, which is modelled as two different electrical resistances, ohmic and polarization, the latter being dependent on the SoC. Since ohmic resistance is almost constant over 20% to 100% SoC, its SoC dependency has not been considered [30]. The model behaves as follows:

$$E = f(\text{SoC}) = E_0 - K \cdot Q_{MAX} \cdot \left(\frac{100}{\text{SoC}} - 1 \right) + A \cdot e^{-B \cdot Q_{MAX} \left(1 - \frac{\text{SoC}}{100} \right)} \quad (2.1)$$

$$R_{POL-discharge} = f(\text{SoC}) = K \cdot \frac{100}{\text{SoC}} \quad (2.2)$$

$$R_{POL-charge} = f(\text{SoC}) = K \cdot \frac{1}{1.1 - \frac{\text{SoC}}{100}} \quad (2.3)$$

where

u is the instantaneous battery voltage [V]

i is the battery current [A] ($i > 0$ when discharging and $i < 0$ when charging)

SoC is the State of Charge of the battery [%]

I_{SELF} is the self discharge current [A]

R_{OHM} is the ohmic internal resistance [Ω]

R_{POL} is the polarization internal resistance [Ω]

C_{POL} is the polarization capacitor [F]

E is the battery open-circuit voltage [V]

E_0 is the open-circuit constant voltage [V]

K is the polarization resistance constant [Ω]

Q_{MAX} is the battery maximum capacity [Ah]

A is the exponential voltage [V]

B is the exponential capacity [Ah^{-1}]

The voltage/runtime model considers the following assumptions: the parameters do

Figure 2.4 Modified model proposed in [36].

not vary for charging and discharging, the Peukert effect and memory effect are negligible, and the ohmic internal resistance is constant.

Thermal model

The Li-ion battery thermal behavior was also improved by Moreno-Torres in [36] with respect to the modified Shepherd model. Temperature is critical when studying battery runtime and ageing, and it also affects power losses and efficiency. Similarly, voltage also depends on temperature. Although the polarization capacitor (polarization time constant) and self-discharge also change with temperature, neither of them are considered, since they do not contribute to energy efficiency and ageing during cycling.

Considering temperature-dependent parameters implies modelling the thermal dynamics of the battery. The thermal model implemented is comprised of two parts: a heat generation model and a heat evacuation model. The first one was developed based on the work presented in [130]. Three heat sources or mechanisms are considered: irreversible heat (or reaction heat), reversible heat, and ohmic heat [31, 49, 159]. Irreversible heat is generated by the transfer of electrons during the electrochemical reaction, reversible heat occurs because of the changes in the entropy of both cathode and anode, and ohmic heat is due to the ohmic resistance of the solid materials and electrolyte. The generated heat inside of a cell can be calculated as follows:

$$H = (E_0 - E) \cdot i + T \cdot \frac{dE}{dT} \cdot i + (R_{OHM} + R_{POL}) \cdot i^2 \quad (2.4)$$

where

H is the heat generated [W]

E is the cell voltage [V]

T is the cell temperature [K]

dE/dT is the change of the equilibrium potential with temperature (varies with SoC)

Other minor sources of heat such as side reactions accounting for ageing are negligible.

Moreover dE/dT is assumed to be constant and greater than 0. The rest of the parameters are temperature dependent:

$$E_0(T) = E_0(T_0) + \frac{dE}{dT} \cdot (T - T_0) \quad (2.5)$$

$$Q_{MAX}(T) = Q_{MAX}(T_0) + \frac{dQ}{dT} \cdot (T - T_0) \quad (2.6)$$

$$K(T) = K(T_0) \cdot e^{\alpha(\frac{1}{T} - \frac{1}{T_0})} \quad (2.7)$$

$$R_{OHM}(T) = R_{OHM}(T_0) \cdot e^{\beta(\frac{1}{T} - \frac{1}{T_0})} \quad (2.8)$$

where α and β are constants for the polarization and internal resistance.

The second part of the thermal model represents the heat evacuation, both within a single cell and for a whole battery pack. As this part highly depends on the specific battery design under analysis (particularly on those aspects regarding the battery pack and its cooling system), the model takes a simplified approach regarding the whole pack. It assumes that both the heat generation and the internal temperature of the cell are constant and uniform, which is a reasonable approximation according to [116]. Hence, the only heat transfer to be modelled goes from the cell surface to the ambient. Strictly speaking, this heat transfer uses two mechanisms, convection and radiation. However, the latter is negligible in this case, which yields the following energy balance equation [31]:

$$H \approx m \cdot c_p \cdot \frac{dT}{dt} + \frac{1}{R_{OUT}} \cdot (T - T_0) + E \cdot \sigma \cdot (T^4 - T_0^4) \Rightarrow R_{OUT} = \frac{1}{h \cdot Ar} \quad (2.9)$$

where

m is the mass of the cell [kg]

c_p is the specific heat capacity of the cell [$J \cdot kg^{-1} \cdot K^{-1}$]

h is the convective heat transfer coefficient [$W \cdot m^{-2} \cdot K^{-1}$]

Ar is the external surface area of one cell [m^2]

σ is the Stefan-Boltzmann constant [$W \cdot K^{-4}$]

Thereby, the temperature variation in a single cell is given by:

$$T(s) = \frac{H \cdot R_{OUT} + T_0}{1 + m \cdot c_p \cdot R_{OUT} \cdot s} = \frac{H \cdot R_{OUT} + T_0}{1 + t_{th} \cdot s} \quad (2.10)$$

where t_{th} is the thermal time constant. In order to model the battery pack evacuation model, the following approximate law was implemented, based on the results provided in [170]:

$$R'_{OUT}(N_S) = \sqrt[6]{\frac{N_S}{2}} \cdot R_{OUT} \quad (2.11)$$

where N_S is the number of cells in series. Since R'_{OUT} is also included in t_{th} , it affects both the steady-state temperature of the cell and the time needed to reach steady-state, increasing both of them.

Ageing model

The ageing of lithium-ion cells has been studied in the literature, and different models have been developed to account for various ageing phenomena, including parasitic side reactions [49], solid electrolyte interface formation [139], and resistance increase [41]. Neither the modified Shepherd model or the model developed by Moreno-Torres included an on-line battery ageing estimation method. The modified Shepherd model is focused on mimicking the battery behavior when subjected to dynamic events. Hence, the performance of the model after a few cycles of usage (cycling ageing), or after a few years (calendar ageing) may not be accurate, since the maximum capacity, internal resistance, and the voltage evolution with SoC, among other parameters, are influenced by the ageing [103]. On the other hand, Moreno-Torres estimates the capacity loss in LiFePO₄ batteries by an Arrhenius type of model, which had been previously introduced in [139]. This model behaves as follows:

$$\nabla Q = B \cdot e^{-\frac{E_a}{R \cdot T}} \cdot Ah^z \quad (2.12)$$

where

∇Q is the capacity loss [%]

B is a pre-exponential factor [-]

E_a is the Arrhenius activation energy [$\text{J} \cdot \text{mol}^{-1}$]

$R = 8.314$ is the gas constant [$\text{J} \cdot \text{mol}^{-1} \cdot \text{K}^{-1}$]

T is the absolute temperature [K]

$z \approx 0.55$ is the power law factor [-]

Ah is the Ah throughput [Ah], defined as:

$$Ah = n \cdot DoD \cdot Q_{MAX} \quad (2.13)$$

where

n is the number of cycles [-]

DoD is the depth of discharge [-]

Equation 2.14 can be linearized, as proposed in [152]:

$$Ln(\nabla Q) = Ln(B) - \frac{E_a}{R \cdot T} + z \cdot Ln(Ah) \quad (2.14)$$

Parameters B , E_a and z are obtained from experimental data, by means of a multi-dimensional regression analysis, which takes multiple capacity curves for different current rates and temperatures into account [111]. Expressions for E_a and B are provided in [152] and [134] respectively, based on experimental results for LiFePO₄:

$$E_a(C_{rate}) = 31500 - 370.3 \cdot C_{rate} \quad (2.15)$$

$$Ln(B) = 1.226 \cdot e^{-0.2797 \cdot C_{rate}} + 9.263 \quad (2.16)$$

The model described, which mainly comes from [139, 152, 134], presents the following behavior:

- The higher the temperature, the faster the capacity loss.
- Ageing with moderate current rates (2C to 4C) is slower than ageing with low current rates (0.5C), and slower than ageing with high current rates (6C and above).
- The model considers that 1 Ah discharged at 100% SoC implies the same capacity loss than 1 Ah discharged at 10% SoC. This is a limitation of many Ah-throughput models [16].
- The model does not consider calendar ageing.

Although the ageing model originally proposed in [152] was intended for constant Crate cycling, the work presented in [134] suggests that it can also be used for cycle life estimation under non-uniform current profiles. Hence, the model was discretized for each value of current rate, including the average value of those rates in the calculation of the capacity loss. During the whole process, the temperature is assumed to be constant.

This ageing model was modified by Moreno-Torres to include temperature variations [36]:

$$Ah(k) = n \cdot DoD(k) \cdot Q_{MAX} \quad (2.17)$$

$$E_a(k) = 31500 - 370.3 \cdot C_{rate}(k) \quad (2.18)$$

$$Ln(B(k)) = 1.226 \cdot e^{-0.2797 \cdot C_{rate}(k)} + 9.263 \quad (2.19)$$

$$T(k) = [mean(T)]_{C_{rate}(k)} \quad (2.20)$$

$$Ln(\nabla Q(k)) = Ln(B(k)) - \frac{Ea}{R \cdot T(k)} + z \cdot Ln(Ah(k)) \quad (2.21)$$

$$\nabla Q = \sum \nabla Q(k) \quad (2.22)$$

where $C_{rate}(k)$ corresponds to each value of the discretized current rate, and $Ah(k)$, $DoD(k)$, $E_a(k)$, $B(k)$, $T(k)$, and $\nabla Q(k)$ are the Ah throughputput, DoD, activation energy, parameter B , temperature and capacity loss for each of the discretized C_{rate} .

In this thesis, the same approach have been followed, but substituting this off-line model (the model calculates the loss capacity once the cycles have been performed by the voltage/runtime model) by an on-line model, that updates the maximum available capacity as the model runs. Hence, there is no need in discretizing it. The model has the same behavior and limitations listed above for the Moreno-Torres model, but it includes the following improvements:

- Ageing is included in the model, so no extra script or code is needed when executing the model. This facilitates the model implementation, and simplifies its usability.
- The model does not depend on the k steps selected for discretization, since C_{rate} is calculated at each instant.
- As the capacity decreases with cycling, the maximum capacity of the battery is updated in the different equations of the model, e.g. equation 2.28.

The model is modified as follows:

$$Ah(k) = \int_{t_i}^{t_f} i(t) \cdot dt \quad (2.23)$$

$$E_a(k) = 31500 - 370.3 \cdot \frac{i(t)}{Q_{MAX}} \quad (2.24)$$

$$Ln(B(k)) = 1.226 \cdot e^{-0.2797 \cdot \frac{i(t)}{Q_{MAX}}} + 9.263 \quad (2.25)$$

where $i(t)$ is the current flowing through the battery. $t_f - t_i$ corresponds to the calculation integration step time, and T is measured at each instant. The next general equation is obtained for each time step:

$$Ln(\nabla Q) = Ln(B) - \frac{Ea}{R \cdot T} + z \cdot Ln(Ah) \quad (2.26)$$

Table 2.2 Selected Li-ion battery parameters.

A123 ARN26650m1			
Voltage	3.3 V	Weight	70 g
Capacity (1C, 25°C)	2.4 Ah	Diameter	26mm
Internal resistance (10 A _{DC})	14 mΩ	Height	65 mm
Maximum continuous discharge	20C	Volume	0.034 l
Standard charge current	1C	Operating temperature	<55°C
Fast charge current	4C	Life (1C, 100% DoD)	>1000 cycles

Moreover, the maximum capacity is modified each instant as follows:

$$Q'_{MAX} = Q_{MAX} - \nabla Q \quad (2.27)$$

Hence, the general voltage equation is modified:

$$E = f(SoC) = E_0 - K \cdot Q'_{MAX} \cdot \left(\frac{100}{SoC} - 1 \right) + A \cdot e^{-B \cdot Q'_{MAX} \left(1 - \frac{SoC}{100} \right)} \quad (2.28)$$

For the analysis developed in section 2.4, results are very similar when this improved ageing model is applied, with respect to the model developed by Moreno-Torres. This happens due to the non dependency of the lost capacity on the SoC of the battery (1 Ah discharge at 100% SoC implies the same capacity loss than 1 Ah at 10% SoC). However, this model improves the general model behavior from a dynamic point of view, and allows for performing studies with aged batteries, since the voltage/runtime behavior is modified accordingly.

LiFePO4 battery: cell parameters and simulation results

A commercial lithium iron phosphate (LiFePO4) cell from A123 was selected for the analysis performed in this chapter. A 3.3V 2.3Ah cell was chosen [29], with the parameters shown in Table 2.2.

Simulation results to prove the consistency of the model are provided in Figures 2.5 and 2.6. The output of the model is checked by comparing the manufacturer's datasheet curves with the output of the model. Figure 2.5 compares the discharge curves at different temperatures for a 1C discharge current.

2.3.2 Supercapacitor model

The EDLC model is obtained from Mathworks in the SimPower toolbox of Simulink [19]. This model is analytical (no look-up tables are needed), non-linear, takes self-discharge into account, expresses the output voltage using a Stern equation, which is represented in Figure 2.7. The model was experimentally validated in [19].

Figure 2.5 Discharge curves at different temperatures comparison between the model implemented in this work and the manufacturer's datasheet. Discharge is performed at 1C.

Figure 2.6 Ageing comparison between the model implemented in this work and the manufacturer's datasheet.

Temperature dependence has not been included in the EDLCs model for three reasons. First, it is not particularly relevant for the purposes of this study (for instance, the ageing of EDLCs is not assessed). Secondly, EDLCs are less sensitive to temperature than batteries. Thirdly, it was assumed that temperature rises in batteries were larger than in

Figure 2.7 SC equivalent circuit developed in [19].

Table 2.3 Selected SC parameters.

Maxwell BCAP310			
Rated voltage	2.7 V	Weight	60 g
Rated capacitance	310 F	Diameter	33 mm
ESR(31 A _{DC})	2.2 mΩ	Height	62 mm
Maximum continuous discharge	41 A	Volume	0.053 l
Maximum current	250 A	Operating temperature	<65°C
Maximum voltage	2.85 V	Life (25°C)	>5 · 10 ⁵ cycles

EDLCs.

Supercapacitor cell parameters

A commercial EDLC cell from Maxwell Technologies (San Diego, CA, USA) was used for all the simulations and analyses performed. Namely, a 2.7V 310F EDLC was chosen [38], with the parameters shown in Table 2.3.

2.3.3 DC-DC converter model

The DC-DC converter modelling is assessed as described in [36]. The topology used for this study is a buck-boost interleaved IGBTs DC-DC converter [59]. The interleaving technique connects DC-DC converters in parallel to split the current flow between two or to create more conversion stages, providing a lag between the pulse-width modulation (PWM) control signals of each converter stage. Its main advantages are constant switching frequency, current ripple reduction, and capacitor and inductor size/weight shrinkage. Higher energy efficiency is also expected from interleaved DC-DC converters when compared to conventional buck-boost converters [8].

Conduction losses [59], IGBTs switching losses [74], and diode turn-off losses are calculated for a constant switching frequency of 5 kHz. Constant losses (control, drivers, and cooling) are not considered. Semiconductor parameters are listed in Table 2.4.

Figure 2.8 Boost interleaved converter [77].

Table 2.4 Semiconductors parameters.

Semiconductors parameters			
IGBTs		Diodes	
V_{ref}	1200 V	V_{ref}	1200 V
I_{ref}	200 A	I_{ref}	200 A
V_{CE0}	0.8 V at 25°C 0.7 V at 150°C	V_{F0}	1.3 V at 25°C 0.9 V at 150°C
r_{CE}	5 mΩ at 25°C 7.5 mΩ at 150°C	r_F	4.5 mΩ at 25°C 6.3 mΩ at 150°C
E_{ON}	21 mJ 600V, 200A, 150°C	E_{RR}	13 mJ 600V, 20A, 150°C
E_{OFF}	27 mJ 600V, 200A, 150°C		

2.3.4 Electric transport model

In order to calculate the power demanded by the load (drive), P_{HESS} , equations 2.29 to 2.32 need to be applied.

$$P_{HESS} = T_{em} \cdot \frac{\omega_{mec}}{\eta_{drive}}(traction), \quad (2.29)$$

$$P_{HESS} = T_{em} \cdot \omega_{mec} \cdot \eta_{drive}(regenerative)$$

where

η_{drive} is the average efficiency of the drive (inverter + machine)

T_{em} is the electromagnetic torque provided by the traction motor, given by:

$$T_{em} - T_{load} = J \cdot \frac{d\omega_{mec}}{dt} + B \cdot \omega_{mec} \quad (2.30)$$

$$J = J_{high} + \frac{J_{low}}{i_{gear}^2} + M \cdot \frac{ERR^2}{i_{gear}^2} \quad (2.31)$$

$$\begin{aligned}
T_{load} &= F_T \cdot \frac{ERR}{\eta_{gear} \cdot i_{gear}} (traction), \\
T_{load} &= F_T \cdot \frac{ERR \cdot \eta_{gear}}{i_{gear}} (regenerative)
\end{aligned} \tag{2.32}$$

where

ERR is the effective rolling radius (which is not the same as the loaded tire radius [104]) [m]

i_{gear} is the transmission gear ratio [-]

η_{gear} is the transmission energy efficiency (assumed to be constant and equal to 0.96 [46]) [-]

J, J_{high} , and J_{low} are the total inertia, total rotatory inertia in the high speed shaft (motor), and the total rotatory inertia in the low speed shaft (wheels) respectively

M is the vehicle mass [kg]

2.3.5 Control strategy

There are two main groups of control strategies to be potentially selected for topology 2 (2.2.1): those based on rules, and those based on advanced control techniques. For instance, a comparison of four rule-based energy management strategies is presented in [2]. On the other hand, advanced control strategies include predictive control algorithms capable of determining a power-mix in real time, based on the expected load demand and loss models for all system components [82] or aiming at the optimization of the system's performance [166].

Topology 2 allows several control possibilities since the DC-DC converter does not have to control the DC-link voltage U_{DC} , which is fixed by the batteries. Due to this restricted flexibility and although advanced control techniques could be explored, the most straightforward way to control the system is with a technique based on rules [27].

This algorithm, which has been implemented in this dissertation, behaves as follows:

1. While motoring, the power demanded by the drive, P_{dem} , is evaluated, and a certain value of P_{Min} is defined for the batteries, depending on their technology. Two main cases are distinguished:
 - (a) If the power demanded by the drive is low, $P_{dem} < P_{MIN}$, then the batteries provide all the traction power. Two sub-cases are considered depending on the EDLC voltage and the vehicle speed:
 - If EDLC $SoC > SoC_{min}$, the EDLCs remain disabled.

- If EDLC $SoC < SoC_{min}$, the batteries also provide power (up to a given value P_{Ch}) to recharge the EDLCs until they reach their minimum value.
 - (b) If the power demanded by the drive is high $P_{dem} > P_{MIN}$, the EDLCs provide all the power but P_{MIN} , which is given by the batteries.
2. While regeneratively braking, EDLCs absorb as much power as possible. Once they are fully charged, the batteries absorb as much power as possible. Finally, conventional brakes deal with the remaining power.

Obviously, the EDLCs' SoC can overrule any of the above rules so that the batteries will take care of any power that cannot be handled by them. In extreme situations (completely full or empty EDLCs), this implies that the HESS will temporarily behave like a conventional ESS.

The control flow diagram is represented in Figure 2.9:

Figure 2.9 Flow diagram for the control strategy presented in [27].

2.4 HESS design methodology and application example

2.4.1 HESS design methodology

There are not many studies comparing HESS in terms of battery ageing and energy efficiency, especially when considering different hybridization grades. This 'hybridization grade' concept refers to the proportion between the energy density storage (batteries) and the power density storage (EDLCs). In this work, the hybridization grade is quantified by means of a magnitude called "hybridization percentage", $HybPer$, which express the

proportion between the EDLCs' weight, W_{ELDC} , referring to the total HESS weight (power converters not included), being W_{BAT} the weight of batteries:

$$HybPer = \frac{W_{ELDC}}{W_{ELDC} + W_{BAT}} \quad (2.33)$$

The HESS design methodology proposed in this thesis, which aims at finding the most suitable $HybPer$ regarding battery ageing and HESS efficiency, can be described as a 'brute-force' optimization methodology. Considering that there are two variables to optimize (battery ageing and HESS efficiency) and one design variable ($HybPer$), this methodology is adequate since the complexity of the problem and the number of cases do not justify the use of a more complex method. Applying a more intelligent optimization methodology does not guarantee reaching a better optimum. The proposed methodology is described in the following steps:

Step 1. Select the hybrid storage technologies, power electronics topology, and control strategy to be operated. A complex topology should not be chosen if the control does not match the topology complexity.

Step 2. Define one or several operation scenarios. In this case, one or several driving cycles.

Step 3. Define the P_{MIN} value for the batteries. This parameter will depend on the technology and most of the time will follow the manufacturer's recommendations.

Step 4. Complete models introducing data corresponding to the particular selected storage devices and vehicle: models of the battery, EDLCs, DC-DC converter, and electric transport model described in Section 2.3 must be completed with data obtained from the HESS designer battery, EDLCs, and DC-DC converter choice, together with the selected electric transport parameters and driving cycles.

Step 5. Perform simulations: an analysis of the complete model must be performed, increasing $HybPer$ in each simulation and measuring HESS efficiency and capacity fade, so both characteristic curves are obtained. If several controls are suitable for implementation, Step 5 should be performed for every control.

Step 6. Combine results in order to find the best $HybPer$ for the HESS design: in order to find the most suitable solution, the results obtained from the performance study should be finally combined in a result function, in which, depending on the relative weight given to the two measurable variables (efficiency and battery capacity fade), a $HybPer$

Table 2.5 Castrosua Tempus Hybrid parameters.

Castrosua Tempus Hybrid Parameters			
Energy	80 kWh	Weight	17.000 kg
Nominal voltage	666 V	Wheel radius	505.7 mm
Nominal capacity	117 Ah	Height	4 m
C_D	0.5	Width	2.5 m
C_F	0.055	Gear reduction	17.65

can be obtained.

2.4.2 HESS dimensioning application example

In order to present how the methodology described in the previous section is applied to a real case, the case study of a Castrosua Tempus Hybrid bus, whose characteristics are presented in Table 2.5, has been chosen for analysis.

The same structure of steps as in Section 2.4.1 will be followed:

Step 1. The Li-batteries and EDLC are defining the HESS. As has been previously introduced, Topology 2 has been selected as the most reliable solution, together with the control described in Section 2.3.5.

Step 2. Different driving cycles have been defined in this example for comparison. The first driving cycle used in this work is one of the ARTEMIS European driving cycles [7]. These cycles were built-up to be representative of the actual conditions of vehicle usage and to reproduce the diversity of the observed driving conditions. Such driving cycles present a real advantage as they are derived from a large database. The chosen cycle consists of two consecutive ARTEMIS urban cycles, with a total duration of 36 min in flat terrain. The net energy consumption is 34 kWh. The driving cycle is represented in Figure 2.10.

The second driving cycle used in this work is the Economic Commission for Europe ECE-15 (Urban Driving Cycle) of the New European Driving Cycle (NEDC) [58]. Although it does not represent real driving conditions, NEDC is still used as a standard driving cycle for testing vehicle emissions. The chosen cycle is a 26-min driving cycle, consisting of two consecutive NEDC urban cycles with a net energy consumption of 28 kWh. NEDC driving cycle is shown in Figure 2.11.

Step 3. Three different values of $PMIN$ have been chosen for the control strategy: 1C, 3C, and 5C.

Figure 2.10 ARTEMIS driving cycle used for this work.

Figure 2.11 NEDC driving cycle used for this work.

Step 4. Battery and EDLCs data, as mentioned, were obtained from [29, 38].

Step 5. Simulink SimPowerSystem has been used for performing the simulation studies. Figure 2.12 shows the general block diagram containing all the different HESS components and the selected EB and cycle power profile.

Figure 2.12 Matlab Simulink SimPowerSystem simulation model.

From the simulation analysis accomplished, several discussions will follow. The HESS global energy efficiencies (batteries, EDLCs, and DC-DC converters) for the ARTEMIS cycle for three different values of P_{MIN} (1C, 3C, and 5C) are displayed in Figure 2.13, whereas the capacity fade after 1000 cycles for the same three cases is illustrated in Figure 2.14. The figures include mean tendency lines for each value of P_{MIN} .

Figure 2.13 HESS global efficiency for topology 2 as a function of the hybridization percentage for three different values of P_{MIN} .

Both figures state that a P_{MIN} value of 3C allows the HESS to work with a higher efficiency and lower battery ageing, showing a maximum efficiency value for a certain $HybPer$ when applied to the specified topology and studied driving cycle. It is noticeable that the battery capacity fade is relevant after 1000 cycles. This happens due to the

Figure 2.14 Battery ageing for topology 2 as a function of the hybridization percentage for three different values of P_{MIN} .

specific relationship between the chosen battery size and the driving cycle, which forces the battery to work with high C_{rate} (above P_{MIN}) once the EDLCs are discharged. The energy efficiency results are shown in Figure 2.15 for topology 2 for the ARTEMIS cycle, with the most efficient control ($P_{MIN}=3C$).

Figure 2.15 DC-DC, DC-DC and Battery, and HESS global efficiency for topology 2 ($P_{MIN}=3C$) as a function of the hybridization percentage.

The points coloured in black is the HESS global efficiency. For low hybridization percentages (0% to 30%), more *HybPer* implies higher efficiency. However, it strongly decreases after reaching its maximum. The curve coloured in blue is the efficiency of the DC-DC converter. As *HybPer* increases (as batteries are replaced by EDLCs, keeping the total weight constant), the converter handles more current, and its average efficiency decreases. Finally, the curve coloured in red is the DC-DC and batteries efficiency. Obviously, for *HybPer*=0%, this value matches the global efficiency since there are no EDLCs, but then, after the maximum efficiency point, it follows a similar tendency as the global efficiency, although keeping its value slightly higher due to the non-influence of the drop in the efficiency of EDLCs.

In order to illustrate the driving cycle dependency for the analysis proposed in this paper, Figure 2.16 compares the global HESS energy efficiency for ARTEMIS and NEDC driving cycles with the same control strategy implemented ($P_{MIN}=3C$). The HESS efficiency improves for both driving cycles compared to a conventional ESS (*HybPer*=0%), reaching their maximum efficiency values at different *HybPer*.

Figure 2.16 HESS global efficiency for topology 2 as a function of the hybridization percentage for two different driving cycles.

The *SoC* of the HESS at the end of the ARTEMIS driving cycle is depicted in Figure 2.17. It is clear that replacing batteries with EDLCs while keeping the weight constant will severely impact the EB range. Figure 2.17 shows this reduction to the point that the driving cycle cannot be finished with *HybPer* $\geq 53\%$.

Figure 2.17 Global *SoC* (batteries and EDLCs) for topology 2 as a function of the hybridization percentage at the end of the ARTEMIS cycle.

Regarding battery ageing, Figure 2.18 shows the capacity loss for different *HybPer* values and for the two driving cycles considered ($P_{MIN}=3C$). 1000 cycles are considered for the ARTEMIS cycle, while, for the NEDC cycle, the number of cycles is 1214, in order to measure the capacity fade after dealing with the same amount of energy.

Figure 2.18 states that there is a considerable difference between both driving cycles when *HybPer* is below 10% and above 30%. It is noticeable that the capacity fade tendency follows the HESS efficiency, decreasing when the HESS efficiency grows. However, the minimum capacity fade does not necessarily match the maximum HESS efficiency at the same *HybPer* point, e.g., for the ARTEMIS cycle, the minimum capacity fade is obtained with a *HybPer* of 17% and the maximum HESS efficiency with 23%, while, for the NEDC cycle, the most suitable *HybPer* is 6%, which minimizes the capacity fade and maximizes the efficiency.

As illustrated with the application example presented in this section, every HESS designer would need to follow the described methodology, running the simulation models after introducing the particular information (type of batteries, EDLCs, DC-DC converter, EB type, or driving cycle) according to the case of study.

Lastly, in order to find the most suitable solution for both HESS designers and companies operating EB fleets, the results obtained from this study should be combined in

Figure 2.18 The battery ageing for topology 2 as a function of the hybridization percentage for two different driving cycles.

a result function. HESS designers, according to the price and availability of battery replacements, the price of the saved energy, the price of EDLCs, etc. together with other circumstances that may occur, should weight the two measurable variables (HESS efficiency and battery ageing), i.e., they should establish the importance they give to each variable so the following result function can be used:

$$y = Weight_1 \cdot (HESS - Eff - curve) + Weight_2 \cdot (C - fade - curve) \quad (2.34)$$

where y is the result curve, $Weight_1$ is the relative importance of the HESS efficiency, $Weight_2$ is the relative importance of the capacity fade, $HESS - Eff$ curve is the HESS efficiency tendency curve, and $C - fade - curve$ is the capacity fade tendency curve. In order to find the $HybPer$ that minimizes cost, the derivative of cost with respect to $HybPer$ needs to be equal to zero.

Taking the ARTEMIS cycle as an example, and with $Weight_1 = Weight_2 = 1$ (both variables are equally important), the result of equation 2.34 is as follows:

$$y = (-0.000232x^3 + 0.011337x^2 - 0.092284x + 87.967338) + (-0.000219x^3 + 0.00043x^2 + 0.167186x + 84.069359) \quad (2.35)$$

where $x = HybPer$. Finally:

$$\frac{dy}{dx} = 0 \Rightarrow HybPer = 20.1423\% \quad (2.36)$$

As has been previously indicated, for the ARTEMIS cycle, the minimum capacity fade is obtained with a *HybPer* of 17%, and the maximum HESS efficiency with 23%, so the obtained *HybPer* is located between both values. It is expected that, changing the variable weights, this *HybPer* will move towards values that improve the behavior of the most important variable. In this case study, changing the HESS efficiency weight to two, while keeping the battery capacity fade weight equal to one, the following result is obtained:

$$\frac{dy}{dx} = 0 \Rightarrow HybPer = 22.1688\% \quad (2.37)$$

2.5 Summary and conclusions

This chapter studies the Li-ion battery ageing in combination with a HESS system formed by batteries and supercapacitors. A HESS dimensioning methodology for electric transport applications is developed, considering all its components and focuses on the hybridization percentage when weight constraints are taken into consideration, since it is not obvious how many EDLCs a HESS should contain (or even if the ESS should contain any EDLCs at all). The proposed HESS dimensioning methodology has potential interest for HESS designers, electric transports manufacturers, and companies operating EB fleets.

First, three HESS topologies have been considered, selecting one as favorite, although some other topology might be chosen depending on the designer's preference.

Then, a deeper analysis has been performed for the selected topology. The complete system under study include a battery pack formed by LiFePO₄ batteries, a SC pack formed by EDLCs, a DC/DC converter, and an equivalent load which represents the electric transport. Mathematical equivalent circuit models for batteries have been described. In this sense, the battery ageing model has been improved so it can be included in the complete battery model (on-line estimation model), and also modifying the battery capacity and, hence, the voltage/runtime performance of the battery.

Moreover, a HESS dimensioning methodology has been proposed, attending to two different criteria: battery capacity fade and global efficiency (batteries, EDLCs, and DC-DC converters). The methodology considers one design variable, hybridization percentage (ratio between the weight of batteries and SCs)

The chapter finishes with a case example of how to implement the proposed methodology for dimensioning an EB HESS. The most studied HESS topology is considered (topology 2), together with a specific rule-based control strategy, for two different driving cycles (ARTEMIS and NEDC).

The results show that there is a different hybridization percentage that minimizes the battery capacity fade and maximizes HESS global efficiency for the ARTEMIS and NEDC cycles, which suggests that there is a most advantageous hybridization percentage for each topology, control strategy, and driving cycle, as has been illustrated by the presented case example. It is important to notice that increasing the hybridization percentage, i.e., increasing the weight of the EDLCs while decreasing the batteries weight, has a huge influence on the driving range, reducing it considerably.

It is also true that, in order to find the most suitable solution, the whole range of HESS topologies and control alternatives have to be considered for a specified cycle, although control strategies are usually developed for a specific HESS topology. This implies that, when designing a HESS and once the driving cycle is known, the HESS topology should be chosen depending on the control strategy that the designer is able to provide so that the hardware complexity matches the software complexity. HESS designers should perform a study like the one proposed in this work in order to find the most suitable solution for their specific application, which should include, in the final stage, a translation to economical terms for maximizing benefits.

3 | Battery Ageing Model for LFP and NMC Chemistries

3.1 Introduction

This chapter focuses on the ageing process occurred in a Li-ion battery. Specifically, this chapter analyzes the modelling process of the capacity decay in a Li-ion battery, which comprises both calendar and cycling ageing. The battery model is part of a complete battery model, which takes into account both voltage/runtime and thermal behavior.

The objectives of this part of the dissertation are the following:

- Develop an on-line ageing model estimation for Li-ion batteries, which is valid for both LFP and NMC chemistries among the family of Li-ion batteries.
- Validate, from a theoretical point of view, the developed ageing model by comparing its performance with previous ageing models.
- Validate, from an experimental point of view, the developed ageing model, by comparing its performance with an NMC battery tested in laboratory.
- Develop a methodology to parameterize the ageing model.

There are three publications derived from this chapter:

- Conference: J. Nájera, M. Blanco, G. Navarro, M. Santos, "Battery Energy Storage System Dimensioning for Reducing the Fixed Term of the Electricity Access Rate in Industrial Consumptions," in *III Congreso Iberoamericano de Ciudades Inteligentes (ICSC-CITIES 2020)*, Soria, Spain, 2020.
- Conference: J. Nájera, M. Lafoz, G. Navarro, J. Torres, "Battery Energy Storage System Dimensioning for Grid Applications According to Power Quality and Battery Ageing," in *II Congreso Iberoamericano de Ciudades Inteligentes (ICSC-CITIES 2019)*, Soria, Spain, 2019.

- Conference: J. Nájera, J. R. Arribas, M. Lafoz, P. Moreno-Torres, R. M. de Castro, “Influence of Different Charging Rates on Li-ion Battery Lifespan: Experimental Validation,” *32nd International Electric Vehicle Symposium (EVS32)*, Lyon, France, 2019.

3.2 Battery ageing models

Li-ion batteries suffer from degradation due to their usage and their exposure to environmental conditions [33, 21, 20, 71]. This degradation, commonly called ageing, affects both the ability of the battery to store energy, and its ability to deliver the power demanded by the load, diminishing both as the ageing increases. Since those two parameters severely limit the battery suitability for a specific application, it is demanded to have information about the evolution of those parameters at any point along its life. Given that capacity and power fade cannot be estimated from common operational data such as SoC, current profile, temperature, etc., estimation models are needed to generate predictions of present and future capacity and power capability [17].

3.2.1 Overview of Li-ion battery ageing mechanisms

Ageing in Li-ion batteries is caused by a large number of factors, affecting the different components of a battery, namely the electrodes, the electrolyte, the separator, and the collectors [149, 10, 1, 72, 148]. Fig. 3.1 shows some of the most studied mechanisms in a Li-ion cell.

Figure 3.1 Degradation mechanisms in Li-ion cells [17].

Li-ion battery materials

In order to describe the Li-ion battery ageing mechanisms, it is required to analyze the anode and cathode materials. Currently, several combination of materials are used within the Li-ion family. Commercial Li-ion batteries present anode materials such as graphite (C), LTO ($Li_4Ti_5O_{12}$), and alloy materials such as Si. On the contrary, various cathode materials are employed, namely Lithium manganese oxide (LMO, $LiMn_2O_4$), Lithium iron phosphate (LFP, $LiFePO_4$), layered metal oxide (NMC, $Li[Ni_xCo_yMn_{1-x-y}]O_2$), and Li rich materials [64]. The different Li-ion battery materials potential is shown in Fig. 3.2. In order to improve the battery energy density, materials with high specific capacity and potential are needed, such as Li-rich materials for the cathode.

Figure 3.2 Potential vs specific capacity of Li-ion battery materials [63, 133].

Presently, LFP/C, LMO/C, NMC/C, and NMC/LTO are the most relevant combinations available. From a general perspective, LFP/C accounts for a higher safety, but low energy and power density. LMO/C has a low lifespan, although its power and energy density are higher. NMC/C has a high energy density, but its safety is not as high as LFP/C. at last, NMC/LTO has a high power performance and improved safety, but a low energy density [90].

Fig. 3.3 shows the US market divided by Li-ion chemistry. The projected development of batteries indicate that NMC, LFP and LCO batteries will be the most popular, being LFP and NMC relevant for industrial applications such as EV and grid connection

batteries, and LCO for mobile electronics. According to this, this chapter is focused on developing an ageing equation that predicts the capacity fade of LFP and NMC batteries.

Figure 3.3 US Li-ion battery market by product [125].

Li-ion ageing mechanisms

The most relevant ageing mechanisms are briefly described in this section, focusing on their influence on the Li-ion battery performance. An approach consisting of a division in ageing related to anode and cathodes materials is taken.

The majority of commercial Li-ion batteries use carbonaceous anodes materials. As seen in Fig. 3.2, the electrolyte stability window goes from 1 V to 4.5 V for organic liquid electrolytes, and the anode working voltage is close to 0.05 V [150], clearly outside of the stability thresholds. Hence, the carbonaceous anode is unstable. During the manufacturing process, the anode presents a crystalline state. When charging the battery for the first few cycles, lithium ions are inserted in the anode and, as a part of a side effect, electrons participate in a decomposition reaction of the electrolyte. The cumulative addition of decomposed materials forms a protective layer on the surface of the anode, commonly known as solid electrolyte interface (SEI) [148, 11].

Theoretically, the SEI only transports lithium ions and prevents electrons transportation, so a stable performance should be expected and further degradation of the electrolyte could be prevented [9]. However, the SEI growth is never stopped, since side reactions cannot be eliminated. This continuous change in the SEI volume forces it to crack, producing a contact between the electrolyte and the lithiated graphite, and resulting in lithium ion consumption and electrolyte decomposition. Thus, the SEI grows continuously, reducing both the battery capacity and increasing the internal resistance

[34]. This SEI formation and growth is widely considered as one of the major reasons involved in the ageing of a Li-ion battery.

From a battery operation point of view, three situations are closely related to the SEI formation [86, 109, 149]. At first, high temperatures in the battery, both storage temperature and working temperature, can lead to a partial SEI dissolution, fostering the electrolyte decomposition. High temperatures also cause the dissolution of the cathode, whose freed ions are transported to the anode, increasing the SEI volume. Moreover, charging the battery with low temperature or overcharging it can lead to the a lithium covering of the graphite particles. The accumulated lithium reacts with the electrolyte, which contributes to the SEI growth and, consequently, to the ageing. At last, cycling the battery with a high DoD can crack the SEI as a consequence of changes in the volume. This behavior, as mentioned, highly contributes to the SEI growth.

The implementation of spinel lithium titanium oxides (LTO) as an anode material is getting attention due to the absence of SEI formation. As seen in Fig. 3.2, it is located in the electrolyte stabilized window. Hence, due to this SEI absence, LTO batteries has great cycle life [91]. However, the high anode potential implies a low cell voltage and low energy density so, depending on the application, selecting LTO batteries may not be recommended.

Regarding the cathode, side reactions are also observed including the electrolyte oxidation over the active material of the cathode, specially for high potential and at high temperatures [78, 95]. The products of these reactions could be solid, creating an interface on the surface of the cathode active particles.

The degradation of the cathode materials comprises processes that depend on the materials that conform it. A common effect observed in the cathode is the volume change during a fast discharge process. For sake of clarity, LFP cathodes can increase its volume up to 6.77% [164]. This causes damages on the cathode structure, leading to loss of active material [35].

Apart from this effect, ionic exchange within the crystalline structure between lithium and iron ions is common in cathodes manufactured with Ni. This prevent from lithium transport, increasing the electrodes impedance [101].

According to the aforementioned ageing processes into consideration, anode ageing is considered to be the main cause for capacity fade and resistance augmentation.

3.2.2 Overview of ageing models for Li-ion batteries

Estimation methods for measuring the battery ageing can be divided into experiment-based methods and model-based methods. The experiment-based method is simple, but a large number of experiments are required to obtain the resistance and capacity change during the aging process. Secondary batteries, i.e. rechargeable batteries, are designed, manufactured and bought for lasting the maximum period of time without compromising their technical behavior. Moreover, the usual charge/discharge rate at which batteries work is low, compared to its capacity, which implies that batteries need several hours to perform a complete charge/discharge cycle ([97, 100]). Due to this situation, performing ageing studies by testing batteries in a laboratory set tend to be highly expensive, since usual charge/discharge profiles are time consuming, and results cannot be evaluated until hundreds of tests are completed. Authors in [160] and [18] used electrochemical impedance spectroscopy techniques (EIS) to evaluate the battery ageing under different operating conditions of C rate and temperature.

On the other hand, the model-based approach is based on battery mathematical models. These models identify battery capacity, internal resistance and other parameters through the parameter identification techniques and are used for examining, explaining or demonstrating ideas and phenomena in a practical and inexpensive way. Firstly, from an economic point of view, ageing models can help to increase the profitability of the application. Secondly, from a design point of view, these models can be applied for developing energy management strategies. At last, from a research perspective, battery ageing models can identify new paths of improvements for optimizing the technology [128].

As previously mentioned in chapter 2, there are three categories of battery models: electrochemical models, intelligent models, and equivalent circuit models. Battery ageing models, conceived as an algorithm that is implemented within a complete model that includes voltage/runtime and thermal behavior among others, can also be categorized in those three groups.

Electrochemical models for SoH estimation are based on the porous electrode theory [39]. Therefore, they can mimic the cell behavior more accurately, and provide information about the battery internal states such as lithium concentration and reactions overpotentials. These battery models usually consist of serials of mutually coupled partial differential equations (PDEs), describing the reaction processes inside the battery [52, 53, 40]. PDEs are computationally expensive, which make the model non-valid for onboard control and estimation algorithms. Hence, a common simplification is made, known as single particle model (SPM), which neglects the battery spatial variation of concentration

and potential. This enables to treat the electrodes as spherical particles subjected to a spatially constant current flux [62, 23]. In [88], an adaptive output-injection observer based on a SPM was published, aiming to estimate the battery SOH in terms of the battery internal resistance variations. Other SoH indicators, apart from internal resistance and capacity, can be applied and are commonly used in SPM ageing models. In this sense, a SPM model linearized over a typical operating range was used in [137] with the implementation of an extended Kalman filter for calculating the lithium bulk and surface concentration variations [167]. Authors in [37] also used the extended kalman filter in a SPM model to estimate the bulk and surface concentrations of the positive electrode. [115] developed a SPM that depended on cell resistance and positive solid phase diffusion time of Li ions, and [171] designed a multi-time-scale observer for SOC and SOH. At last, authors in [158] developed and validated a SPM model that estimates SOH by means of a quantitative correlation between a set of aging characteristic parameters and the remaining capacity. Going through the cited electrochemical models, a common limitation is the difficulty to obtain information for parameterizing the SPM models, which restricts their capacity to measure the variation of the chosen SOH indicators during the whole battery life-time. In other words, they lack data support to depict the variation trend of the indicators. Moreover, the computational effort, even though it is reduced with SPM models, is still much higher than equivalent circuit models [158].

Intelligent models for battery ageing estimation, also called self-adaptive models, arose as a solution for minimising the testing labours required for parameterize and validate electrochemical and equivalent circuit models. Theoretically, a self-adaptive model can be understood as a model that is able to update and correct itself so it fits the newest available data samples, and predict further battery ageing [92]. A reduced laboratory test is needed for developing a preliminary model, which will be updated based on operational data, commonly extracted from a data acquisition system installed inside the EV. There are several techniques that can be applied when developing a self-adaptive battery ageing model, which differ on the updating approach: Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Gaussian Process Regression (GPR), Relevance Vector Machine (RVM), and Artificial Neural Network (ANN). An ARIMA model was developed and validated in [168] and [87], improving the absolute error accuracy of previous self-adaptive models by using state-of-health (SOH) time series to predict the global deterioration trend, while having a low computational effort. SRV, a well-known machine learning method, is used in [107], [102], and [106] for developing an ageing estimation method. Results are satisfactory, although the SVR technique seems to be highly influenced by environmental and load conditions [138]. The GPR approach considers every possible parametric class simultaneously, so it becomes a non parametric model [118]. They are commonly developed as a Bayesian non-parametric method with

predictive capability, and are able to provide a really high accuracy. Works published in [127] and [66] use the GPR technique. RVM technique is based on the idea that the training data points that are not contributing to describe the battery ageing trend should be removed [118]. Hence, a sparse model is created, where the remaining data are called relevant vectors. Works published in [161], [169], and [165] use this RVM technique, which improves the probabilistic character of the estimation that occurred in the SVM models. ANN approach includes a wide variety of learning machines, formed by neurons that are fed by several inputs, which are transformed by an activation function, and then sent to the next layer. The back-propagation algorithm is one of the most popular, used in the publications [69], [120], and [119]. Considering all self-adaptive techniques, a common feature is that they depict the nonlinear relationship between the ESS performance and its influencing factors, without a detailed understanding of the reactions inside the ESS. The major limitation is that they need an enormous amount of data so the ageing model can be accurate on its prediction.

Equivalent circuit models, also called semi-empirical models (SEM), use mathematical expressions such as linear, exponential, Eyring and Arrhenius equations, to capture the cycling and calendar ageing. The works published in [131] and [153] proposed SEMs based on the Arrhenius law to estimate battery ageing of NMC batteries. Parameters were calculated based on laboratory test matrixes that considered DoD, temperature, and C rate, reaching a high accuracy (less than 5% of error) with the proposed expression. Authors in [110] developed a degradation estimation model considering SoC and temperature, which was successfully applied for vehicle-to-grid applications. An Eyring acceleration model was developed in [122], focusing on investigating the effects of the SOC drifting on the battery calendar degradation. The work developed in [103] successfully developed and validated a LPF ageing model based on an Arrhenius law. Another SEM was published in [146], where the authors validates a modified equivalent-circuit model with a battery ageing estimator, which presents a reasonable good behavior for controlled conditions, i.e. C rates below 2C and temperatures between 25°C and 45°C. SEM are widely used due to their simpler structure, and due to its facility to be parameterized when compared to electrochemical models, and the low amount of data needed when compared with intelligent models. Their prediction accuracy, even though is generally lower than the models developed with the aforementioned techniques, remains below 5%, which is considered as satisfactory for most of the applications.

According to the objectives defined for this chapter, which is developing a general expression for LFP and NMC chemistries among the Li-ion family, SEM technique has been selected, aiming for a general ageing expression which, although not perfectly accurate neither for LFP nor NMC, is accurate for predicting their ageing. Moreover, the model

should be easily parameterizable with few data, which also justifies the selection of SEM techniques.

3.3 Ageing model description for LFP and NMC

3.3.1 Calendar and cycling ageing

From a practical point of view, the battery ageing in semi-empirical models has been traditionally divided in calendar and cycling ageing.

Calendar ageing

Calendar ageing can be defined as the degradation suffered by the battery over time, whether it has been working or not. It is extensively reported in the literature that the main variables that influence the calendar ageing are, besides time, the temperature and SoC. These variables affect in a different way depending on the specific chemistry of the battery. As several authors have described, the calendar ageing follows an Arrhenius exponential equation (equation 3.1) [110, 129, 123]:

$$\text{Ln}(\nabla Q_{cal}) = a \cdot e^{b \cdot \text{SoC}} \cdot e^{c/T} \cdot t^z \quad (3.1)$$

where ∇Q_{cal} is the loss capacity due to calendar ageing, a , b , and c are constants that depend on the battery chemistry, SoC is the State of Charge, T is the battery temperature, t is the time, and z is an exponential parameter that can take values between 0.5 and 1.

Even though equation 3.1 is widely employed, there are slight modifications proposed by other authors. Authors in [43] substitute the SoC by the open circuit voltage, which is directly related with the former variable.

Calendar ageing studies in laboratory are performed by keeping several identical cells at different temperatures and different SoC. Periodically, a capacity test is performed so the battery degradation can be measured. A common calendar ageing test is performed in [129], whose results are shown in Fig. 3.4.

Table 3.1 presents a literature revision based on the work developed by [57], where the importance of the different variables over the calendar ageing can be seen. The relevance of the stress factors on the calendar aging effects ΔC or ΔR is qualitatively classified as having no influence, minor influence, or strong influence. Given that the specific Li-ion chemistry has a significant impact, this aspect is also highlighted.

Figure 3.4 Typical calendar ageing test results [129].

Table 3.1 Relevance of the stress factors on the calendar aging. Based on [57].

Stress Factor	Chemistry	Factor Range	Influence on ΔC	Influence on ΔR	Reference
T	NCA	10-40°C	Strong	-	[75]
	NCA		Strong	Strong	[21]
	NMC	0-5°C	Strong	Strong	[132]
	NMC, LFP	40-70°C	-	Strong	[96]
	LFP		Strong	Strong	[61]
			Strong	Strong	[149]
			Strong	Strong	[13]
	LFP		No	Minor	[61]
	NCA		Strong if high T	Strong if high T	[21]
	NCA	0-100%	Strong	-	[75]
Fluctuations in T SoC	NMC	0-100%	Strong	Strong	[132]
	NMC,LFP	20-100%	-	Strong	[96]
			Strong	Strong	[149]
		80-100%	Strong	Strong	[13]

Cycling ageing

Cycling ageing can be defined as the degradation that the battery suffers when it is working, i.e. when there is current flowing through its terminals. This ageing depends on the battery utilization, i.e. the power profile that the battery is working with, the chemistry of the battery, and the temperature. Hence, several factors are involved, some of them superposed with the calendar ageing factors.

Regarding temperature, its effects on the battery ageing while cycling have been widely reported, inducing a high degradation with both high and low temperatures. The utilization of the battery is commonly measured by the DoD, representing the capacity variation along one cycle.

Table 3.2 Relevance of the stress factors on the cycling aging. Based on [57].

Stress Factor	Chemistry	Factor Range	Influence on ΔC	Influence on ΔR	Reference
T	NCA	10-40°C	Strong	-	[75]
	LFP	25-55°C	Strong	-	[142]
	LFP		Strong	Strong	[61]
			Strong	Strong if high T	[149]
Fluctuations in T			-	Strong	[13]
	LFP		No	Minor	[61]
	NCA, NMC		Strong	No	[21]
	NMC	1-2C	No	No	[96]
$I_{discharge}$	LFP	1-6C	No	No	[96]
	LFP		Minor	High	[61]
	LCO	0.6-3C	Minor	-	[61]
			Strong	Strong	[149]
Mean SoC	NCA	33-78%	Strong	-	[75]
	LFP		Strong if high mean SoC	Strong	[149]
	LFP		No	Minor	[61]
		80-100%	-	Strong	[13]
$SoC_{end-of-discharge}$	LFP		No	No	[61]
$SoC_{end-of-charge}$	LFP		Minor	Strong	[61]
ΔDoD	NCA	25%	Strong	-	[75]
	NMC, LFP	20-80%	Minor	Minor	[96]
	LFP		No	Minor	[13]
	LFP		Strong	Strong	[61]
			-	Strong	[108]
			Strong	-	[149]

Table 3.2 presents a literature revision based on the work developed by [57], where the importance of the different variables over the cycling ageing can be seen, with the same format as the one used for calendar ageing.

The information gathered in the table allows for obtaining an important conclusion: it is not possible to obtain a general expression for every chemistry. Moreover, authors focus on different variables to take ageing into account. For the cycling ageing there is no a single equation that relates degradation with the variables that cause it, as happened with calendar ageing. A comparative table with the different semi-empirical models is presented in Table 3.3. Apart from the chemistry, the different variables included in each model are detailed in the Table.

For cycling ageing, the input parameters considered in the different models are diverse, which confirms the observation drawn before. Moreover, it is noticeable that only few authors detail the relative importance or influence of the chosen input parameters. The majority of them do not detail the choice of the parameters. The two most cited equations, as well as the two most detailed expressions are listed as follows for LFP and NMC chemistries:

$$Ln(\nabla Q_{cyc}) = B(C_{rate}) \cdot e^{-Ea/RT} \cdot Ah^{0.55} \quad (3.2)$$

Table 3.3 Comparative of the semi-empirical battery ageing models. Based on [57].

Reference	Chemistry	Input						Output	
		T_{cal}	SoC_{cal}	T_{cyc}	$I_{dis-cyc}$	SoC_{cyc}	ΔDoD_{cyc}	ΔC	ΔR
[110]	NCA, LFP	x	x	x	x			x	x
[12]	NCA, NMC	x	x	x	x		x	x	x
[153]	NMC	x		x	x		x	x	
[43]	NMC	x	x					x	x
[131]	NMC	x	x			x	x	x	x
[68]	NMC	x	x	x		x	x	x	
[96]	NMC, LFP	x	x				x	x	x
[152]	LFP			x	x		x	x	
[61]	LFP	x	x		x		x	x	x
[60]	LFP	x	x					x	
[141]	LFP	x	x						x

$$Ln(\nabla Q_{cyc}) = (a \cdot T^2 + b \cdot T + c) \cdot e^{(d \cdot T + e) \cdot C_{rate}} \cdot Ah \quad (3.3)$$

where

∇Q_{cyc} is the loss capacity due to cycling ageing [%]

a, b, c, d , and e are constants that depend on the battery chemistry [-]

Ah are the ampere-hour flown in and out of the battery [Ah]

T is the battery temperature [K]

B is a pre-exponential factor [-]

C_{rate} is the charge/discharge current of the battery referred to its nominal capacity [-].

E_a is the Arrhenius activation energy [$J \cdot mol^{-1}$]

$R = 8.314$ is the gas constant [$J \cdot mol^{-1} \cdot K^{-1}$]

3.3.2 Combined ageing model

As it has been detailed in the last section, several semi-empirical models have been proposed in the literature. Those models differ both in the proposed functional equation, and in the input variables of the model. In this section, a new general equation is proposed, valid for LFP and NMC chemistries, and taking into account, directly or indirectly, the variables that cause the battery degradation.

Proposed form for the ageing equation

A functional equation is proposed in this section for the battery capacity loss, explaining the motivation and the physical meaning of the input variables. The proposed equation considers both calendar and cycling ageing.

$$Q_{loss} = Q_{cal} + Q_{cyc} \quad (3.4)$$

At first, calendar ageing is modeled as expressed by equation 3.5. This expression, as previously explained, is widely accepted among the scientific community, given that the calendar ageing follows an Arrhenius equation.

$$Q_{cal} = a \cdot e^{b \cdot SoC} \cdot e^{c/T} \cdot t^z \quad (3.5)$$

where

Q_{cal} is the lost capacity due to calendar ageing [%]

a , b , and c are parameters dependent on the battery chemistry

SoC is the State of Charge of the battery [%]

T is the battery temperature [K]

t is the time in days [day]

z is the power law factor [-], which can take values between 0.5 and 1

The physical meaning of the variables is described as follows:

- Time: according to the definition of calendar ageing, this ageing occurs due to the passage of time, either if the battery is being used or not. Hence, including time in the equation seems a logic approach when modelling calendar ageing.
- Temperature: As previously explained, a high temperature induces a partial dissolution of the SEI interface, among other phenomena that increase the decomposition of the electrolyte and, hence, the battery degradation. This effect is also present on a battery when it is not working. Thus, it is reasonable to include temperature in the calendar ageing equation. The exponential influence of temperature has been extensively reported in the literature [111, 110, 152]. Notice that, in order to obtain a battery degradation caused by a temperature increment, constant c in equation 3.5 must be negative.
- State of Charge (SoC): According to the studies performed by the authors cited in Section 3.3.1, a battery suffers a higher degradation when kept at higher SoCs. Moreover, it follows an exponential distribution. Notice that constant c in equation 3.5 must be positive.

For cycling ageing, there are only eight authors that proposed an equation for this kind of ageing. From a physical point of view, the one considered the most suitable for modelling the cycling ageing is equation 3.6:

$$Q_{cyc} = (a \cdot T^2 + b \cdot T + c) \cdot e^{(d \cdot T + e) \cdot C_{rate}} \cdot Ah \quad (3.6)$$

where

Q_{cyc} is the lost capacity due to cycling ageing [%]

a , b , c , d , and e are parameters dependent on the battery chemistry

T is the battery temperature [K]

C_{rate} is the charge/discharge rate []

Ah is the Ah throughoutput [Ah]

The physical meaning of the variables is described as follows:

- Ah: according to the definition of cycling ageing, this ageing occurs due to the current flow through the battery terminals. Hence, including current flow per unit of time in the equation seems a logic approach when modelling cycling ageing. According to [110, 152, 153], the battery degradation must be directly proportional to the Ah throughoutput.
- Temperature: As previously explained, for a working battery, a high temperature triggers several phenomena that increase the rate of electrolyte decomposition and, hence, the battery degradation. Moreover, working with low temperatures can induce a lithium cover in the graphite particle, which enhances the degradation process. According to this, there is an optimum range of temperatures for a battery, and working out of its bounds accelerates the degradation. This effect can be modelled by a second grade polynomial, as the one included in equation 3.6. This parabola must be concave and cannot cut the real axis at any point, given that degradation cannot be negative. Moreover, the parabola minimum point represents the optimum working temperature for the battery.
- C rate: the current flow through the battery terminals ages the battery, but the rate at which it happens is also important. This is evident, since if no degradation occurs due to the current flow rate, all Li-ion batteries could charge at maximum rate, which is a practice that battery manufacturers are clearly against. The relation between degradation and C rate is exponential, according to the authors cited in Section 3.3.1. On the other hand, there is a docking effect between temperature and C rate associated to certain electrochemical processes in the battery. This effect is specially observed when the battery works with high C rates and consists of the following: although the battery degradation grows as the C rate increases, the degradation rate diminishes with temperature. This is mathematically expressed in 3.6. Notice that this term must be negative so the battery degradation diminishes with temperature.
- ΔSoC : even though this variable is not explicit in 3.6, its effects are indirectly expressed. According to [83], the effect of the SoC variation during a cycle can

be divided into SoC_{avg} and SoC_{dev} . For a specific cycle, the former indicates the average SoC during that cycle, and the latter the SoC deviation with respect to the SoC_{avg} . Increasing both SoC_{avg} and SoC_{dev} produce a higher degradation, i.e. the deeper the cycling and the higher the SoC, the higher the capacity loss. These effects are already taken into account in equation 3.6, since a deeper cycling imply a higher Ah flow through the battery terminals. The effect of the SoC_{avg} has already been taken into account in equation 3.5, corresponding to calendar ageing.

Summarizing, the general equation proposed is presented as follows:

$$Q_{loss} = (a \cdot T^2 + b \cdot T + c) \cdot e^{(d \cdot T + e) \cdot C_{rate}} \cdot Ah + f \cdot e^{g \cdot SoC} \cdot e^{h/T} \cdot t^z \quad (3.7)$$

where

Q_{loss} is the total lost capacity [%]

a, b, c, d, e, f, g , and h are parameters dependent on the battery chemistry [-]

T is the battery temperature [K]

C_{rate} is the charge/discharge rate [-]

Ah is the Ah flown through the battery [Ah]

t is the time in days [day]

z is the power law factor [-], which can take values between 0.5 and 1

3.4 Capacity fade simulation model

Equation 3.7 has been implemented in the battery model described in chapter 2. The capacity model used for the HESS dimensioning study in chapter 2 only accounted for cycling ageing, and was only valid for LFP batteries. This new capacity fade model extends its applicability to NMC batteries, and includes calendar ageing.

Simulation model developers usually find a common problem when implementing ageing models as the one described by equation 3.7. This difficulty lies in the fact that the equation allows to determine the battery ageing if the working conditions remain constant, which is highly improbable in the case of a battery, where C_{rate} , SoC , and T are constantly changing whit its use.

This circumstance imply that, if equation 3.7 is directly implemented, the capacity fade suffers an abrupt and slight increment or decrement every time the working conditions change. This behavior is not realistic, since the capacity fade should decay continuously, not to mention that a nominal capacity increment is physically impossible. Note that a momentary capacity increment can be experienced in the battery at high working tem-

peratures, as seen in chapter 2, but an increment in the nominal capacity is not possible.

To solve this problem, the approach described as follows has been taken. Equation 3.6 can be rewritten as follows, considering that C_{rate} , SoC , and T vary with time as the battery is being used:

$$Q_{cyc} = f(T(t), C_{rate}(t)) \cdot I(t) \cdot t \quad (3.8)$$

where its application is valid if f is constant over time, and only $I(t)$ varies. In order to obtain the capacity fade when f is not constant, a time differential dt can be taken where $f(t)$ remains constant, so the lost capacity during that dt equals:

$$dq_{cyc} = f(T(t), C_{rate}(t)) \cdot I(t) \cdot dt \quad (3.9)$$

Hence, the capacity lost due to cycling ageing over a finite time will be the addition of every dq_{cyc} obtained with equation 3.9, which can be implemented in the simulation model:

$$Q_{cyc} = \int_{t_f}^{t_i} dq_{cyc} = \int_{t_f}^{t_i} f(T(t), C_{rate}(t)) \cdot I(t) \cdot dt \quad (3.10)$$

An identical approach can be taken for the calendar ageing expression. Equation 3.5 can be rewritten as:

$$Q_{cal} = g(T(t), SoC(t)) \cdot t^2 \quad (3.11)$$

where, assuming $u = t^2$, can be rewritten again as:

$$Q_{cal} = g(T(u), SoC(u)) \cdot u \quad (3.12)$$

Again, this equation can only be applied when $g(u)$ remains constant over time. Taking a differential du where $g(u)$ remain constant, the capacity loss due to calendar ageing can be expressed as:

$$dq_{cal} = g(T(u), SoC(u)) \cdot du \quad (3.13)$$

Hence, the capacity lost due to calendar ageing over a finite time will be the addition of every dq_{cal} obtained with equation 3.13, which can be implemented in the simulation model:

$$Q_{cal} = \int_{t_f}^{t_i} dq_{cal} = \int_{t_f}^{t_i} g(T(t), SoC(t)) \cdot z \cdot t^{z-1} \cdot dt \quad (3.14)$$

Table 3.4 Tests matrix for parameterizing the calendar ageing model

	$SoC - 1$	$SoC - 1$
$T - 1$	Test 1	Test 2
$T - 2$	Test 3	Test 4

3.5 Model parametrization

3.5.1 Parametrization methodology

The model needs to be parameterized so it can be applied to a specific battery. As a result of the parametrization, fixed values for parameters a to h are obtained. Given that the proposed ageing model corresponds to the semi-empirical models category, several laboratory tests need to be performed. In this sense, independent test matrixes can be defined for calendar and cycling ageing.

For calendar ageing, a minimum of 4 laboratory tests are needed for parameterizing f , g , and h :

- Two tests with two different SoC ($SoC - 1$ and $SoC - 2$) and at a fixed temperature ($T - 1$)
- Two tests with the same SoC as the previous tests ($SoC - 1$ and $SoC - 2$) at a new fixed temperature ($T - 2$)

Hence, the tests matrix shown in Table 3.4 with the minimum number of tests is obtained. Ideally, one of the selected temperatures, either $T - 1$ or $T - 2$ should be close to $23^{\circ}\text{C} - 25^{\circ}\text{C}$, which corresponds to the usual preferred temperature for Li-ion batteries. Moreover, even though the minimum number of tests is 4, the higher the number of performed tests, the better the parameter adjustment. Thus, the tests matrix can be expanded both in number of selected SoC and temperatures.

Calendar ageing tests must be performed by leaving a cell or battery in a room or chamber at the selected SoC and temperature several days, and periodically performing a complete capacity tests with the procedure recommended by the manufacturer.

On the other side, a minimum of 5 tests are needed for parameterizing the cycling ageing:

- Three tests at a fixed C rate ($C_{rate} - 1$) and a fixed DoD ($DoD - 1$) at three different temperatures ($T - 1$)

Table 3.5 Tests matrix for parameterizing the cycling ageing model

	$T - 1$	$T - 2$	$T - 3$
$C_{rate} - 1$ and $DoD - 1$	Test 1	Test 2	Tests 3
$C_{rate} - 2$ and $DoD - 1$	Test 4		
$C_{rate} - 3$ and $DoD - 1$	Test 5		

- Two tests with the same DoD ($DoD - 1$) but with new C rates ($C_{rate} - 2$ and $C_{rate} - 3$) and at a fixed temperature ($T - 1$)

The resulting test matrix is shown in Table 3.5, where the first set of three tests allow for obtaining parameters a to c , and the second set for d and e . The tests must be performed at a cell or battery with the selected conditions in terms of DoD, C rate and temperature. A complete capacity tests with the procedure recommended by the manufacturer is needed periodically to measure the capacity loss as a function of Ah or cycles.

As happened with the calendar ageing matrix, the cycling ageing matrix can be expanded and completed with more laboratory tests. As aforementioned, a higher number of tests leads to a better parameter adjustment, expanding the range of conditions in which the parameters perform accurately. Nevertheless, increasing the number of both calendar and cycling tests results in a considerable increment in time, since several number of days and cycles are needed to observe variations in the capacity. Moreover, the tests are destructive for the battery. Hence, these two factors imply a cost that must be taken into account when designing the test matrixes, so a compromised solution between the accuracy range of the parameters and the investment in time and battery or cells degradation should be considered.

Once the tests have been performed, the last step consist of obtaining the parameters. Each capacity measurement taken from the tests gives an equation, so an overdimensioned no linear system is obtained. A least square methodology is proposed in this dissertation for solving this system, which has been programmed in MATLAB and solved through the LMFsolve function.

3.5.2 Model parametrization examples

In order to exemplify this parametrization methodology, two cases, one for an LFP and one for NMC battery, are detailed in this section.

Model adjustment for an LFP battery

The data provided in [123] and [103] for a cylindrical cell of 3.3 V and 2.3 Ah has been selected for exemplifying the methodology for an LFP battery.

In order to parameterize the calendar ageing equation, the tests performed by Redondo-Iglesias et.al with three different values of SoC and temperature are selected [123]. The obtained values for calendar ageing parameters are the following:

$$f = 5.9808 \cdot 10^6$$

$$g = 0.6898$$

$$h = -6.4647 \cdot 10^3$$

$$z = 0.5$$

The calendar ageing model adjustment to the data provided by [123] with the calculated parameters is shown in Fig. 3.5, Fig. 3.6, and Fig. 3.7.

Figure 3.5 Calendar ageing model adjustment to a standard LFP battery at 30°C.

Parameter z , which can take values between 0.5 and 1, requires an additional explanation. For tests with high temperatures ($T = 60^\circ\text{C}$), low values of z showed a better adjustment of the model for few days of ageing (below 100 days), and high values of z performed better for longer periods of time. After analysing the three cases at 60°C , the optimum value for z was 0.75. However, a value of 0.5 was selected given that at high temperatures the degradation reaches a 20% of capacity decay in few days. Thus, it is worth to adjust the model for short number of days.

Figure 3.6 Calendar ageing model adjustment to a standard LFP battery at 45°C.

Figure 3.7 Calendar ageing model adjustment to a standard LFP battery at 60°C.

Even with this z parameter selection, high temperatures are adjusted much worse than 30°C and 45°C. Nevertheless, this behavior should not alarm potential users of the model, since keeping a battery at temperatures higher than 45°C for long periods of time is unusual, and strongly discouraged by manufacturers.

Once the values for the calendar ageing parameters have been obtained, the calendar

ageing parameters can be extracted from the data provided in [123] and [103].

Cycling ageing parameters obtained using each of those data sets were identical, as expected. The obtained values for cycling ageing parameters are the following:

$$a = 2.0916 \cdot 10^{-8}$$

$$b = -1.2179 \cdot 10^{-5}$$

$$c = 0.0018$$

$$d = -1.7082 \cdot 10^{-6}$$

$$e = 0.0556$$

Fig. 3.8, Fig. 3.9, and Fig. 3.10 show the model adjustment to the data provided by Redondo-Iglesias et.al in [123], where tests with 0.5C, 2C and 6C were performed at different temperatures. Results are presented as a function of the Ah flown through the cell, although it could be easily represented as a function of cycles if needed, with the following relation:

$$Ah = n \cdot DoD \cdot Q \Rightarrow n = \frac{Ah}{DoD \cdot Q} \quad (3.15)$$

Figure 3.8 Cycling ageing model adjustment to a standard LFP battery at 0.5C.

Figure 3.9 Cycling ageing model adjustment to a standard LFP battery at 2C.

Figure 3.10 Cycling ageing model adjustment to a standard LFP battery at 6C.

Model adjustment for an NMC battery

The data provided in [153] by Wang et.al for a commercial cylindrical NMC cell of 1.5 Ah and 3.7 V, has been selected for exemplifying the methodology for an NMC battery.

For parameterizing the calendar ageing model, 4 tests at different temperatures were

performed, but no SoC variation was included. As previously explained in the parameterizations methodology, SoC variation must be taken into consideration, so a minimum of 2 different SoCs and 2 different temperatures are tested. For NMC batteries, the SoC at which the NMC batteries are kept has minimum relevance, in contrast with LFP batteries. Hence, taking into consideration temperature and time is sufficient for modeling calendar ageing in NMC cells, as explained in reports [156] and [20].

The obtained values for calendar ageing parameters are the following:

$$f = 154.9601$$

$$g = 0.6898$$

$$h = -2.9467 \cdot 10^3$$

$$z = 0.5$$

The calendar ageing model adjustment to the data provided by [153] with the calculated parameters is shown in Fig. 3.11.

Figure 3.11 Calendar ageing model adjustment to a standard NMC battery at 30°C.

Cycling tests were also performed by Wang et.al in [153]. The obtained values for cycling ageing parameters are the following:

$$a = 1.2918 \cdot 10^{-7}$$

$$b = -7.6878 \cdot 10^{-5}$$

$$c = 0.0114$$

$$d = -6.7149 \cdot 10^{-3}$$

$$e = 2.3467$$

Fig. 3.12, Fig. 3.13, 3.14, and Fig. 3.15 show the model adjustment to the data provided by Wang et.al, where tests with 0.5C, 2C, 3.5C, 5C, and 6C were performed at 10°C, 20°C, 34°C, and 46°C. Results are presented as a function of the Ah flown through the cell.

Figure 3.12 Cycling ageing model adjustment to a standard NMC battery at 10°C.

3.6 Theoretical validation of the capacity fade model

Once the capacity fade model has been included in the complete battery model in Simulink (Section 3.4) and its parametrization methodology has been developed and tested (Section 3.5), it needs to be validated. This section includes a theoretical validation of the capacity fade model, preceded by the dynamic and thermal electrical model validation for LFP and NMC batteries.

3.6.1 Theoretical validation of the electrical battery model

The dynamic and thermal electrical models, described in chapter 2, are validated here for both an LFP and an NMC cells. The electrical model can be parameterized from each cell

Figure 3.13 Cycling ageing model adjustment to a standard NMC battery at 20°C.

Figure 3.14 Cycling ageing model adjustment to a standard NMC battery at 34°C.

data sheet, following the methodology proposed in [130, 144, 170] with the data provided in the data sheet.

The already described A123 LFP battery used in chapter 2 was already validated, and the model validation comparing the discharge curves at different C_{rate} and its thermal behavior to the ones provided in the manufacturer's data sheet are summarized and dis-

Figure 3.15 Cycling ageing model adjustment to a standard NMC battery at 46°C.

Table 3.6 Selected LFP battery parameters.

A123 ARN26650m1			
Voltage	3.3 V	Weight	70 g
Capacity (1C, 25°C)	2.4 Ah	Diameter	26mm
Internal resistance (10 A _{DC})	14 mΩ	Height	65 mm
Maximum continuous discharge	20C	Volume	0.034 l
Standard charge current	1C	Operating temperature	<55°C
Fast charge current	4C	Life (1C, 100% DoD)	>1000 cycles

played in Fig. 3.16 and 3.17 respectively, with the parameters provided in Table 3.6.

The model allows for a precise adjustment for low and medium C_{rates} , given that 10A corresponds to a C_{rate} greater than 4C. Discharge curve at 30A, corresponding to a C_{rate} of 13C is not well represented by the model. However, 13 C is not a usual discharge rate, and a battery will only reach this rate during very low periods of time, never continuously. Hence, the model can be considered satisfactory for representing the voltage-runtime behavior of an LFP battery.

The thermal behavior is also satisfactorily validated, since a minimum error is achieved when compared with the data provided by the manufacturer.

A Kokam NMC battery has been selected to validate the model adjustment to an NMC battery, whose parameters are listed in Table 3.7. The model performance comparison to

Figure 3.16 LFP battery discharge model adjustment to manufacturer's curves, at $T = 25^{\circ}\text{C}$ for different discharge rates.

Figure 3.17 LFP battery thermal model adjustment to manufacturer's curves, at 1C for different temperatures.

the manufacturer's data sheet curves, both discharge and temperature, are displayed in Fig. 3.18 and 3.19 respectively.

Regarding an NMC battery, the model adjusts the thermal model with precision, al-

Table 3.7 Selected NMC battery parameters.

Kokam SLPB100255255HR2			
Voltage	3.7 V	Weight	1450 g
Capacity (0.2C, 23°C)	55 Ah	Length	265mm
Internal resistance (1kHz)	0.6 mΩ	Height	276mm
Max. continuous discharge	12C	Thickness	13.3mm
Max. continuous charge	3C	Discharging T	-20°C to 55°C
Storage temperature	-20°C to 25°C	Life (1C, 100% DoD)	>7000 cycles

though for low temperatures close to 0°C and below, the deviation at the end of the discharge increases. Nevertheless, operation temperatures close to 0°C are not recommended by the manufacturer, and are far from the normal operating temperature.

The NMC voltage-runtime model adjustment presents a low error for C_{rates} equal to 2C and below. For relative capacities above 80 % the model losses accuracy. However, the relative error remains below 4% even for that part of the curve, so the adjustment is considered satisfactory. For C_{rate} above 2C, the model loses precision, reaching a maximum of 6.88% of relative error for a 5C discharge. The model is considered satisfactorily validated for low and medium C_{rate} , and errors higher than 5% can be achieved for a continuous discharge with high C_{rate} which, as commonly stated by battery manufacturers, is not a usual and recommendable operation for a battery.

Figure 3.18 NMC battery discharge model adjustment to manufacturer's curves, at $T = 25^\circ\text{C}$ for different discharge rates.

Figure 3.19 NMC battery thermal model adjustment to manufacturer's curves, at 0.5C for different temperatures.

3.6.2 Theoretical validation of the capacity fade model

Once the electrical model has been validated, a similar procedure can be applied to the capacity fade model. Hence, a theoretical validation comparing the model outcome with the capacity fade data provided by the battery manufacturers in the data sheets is performed. The model is validated for both LFP and NMC chemistries.

Capacity fade model validation for an LFP battery

For the LFP chemistry, the A123 battery model ANR26650M1 used for the electrical model validation is selected. The capacity fade model was parameterized in 3.5 for this specific battery, with the following parameters:

$$a = 2.0916 \cdot 10^{-8}$$

$$b = -1.2179 \cdot 10^{-5}$$

$$c = 0.0018$$

$$d = -1.7082 \cdot 10^{-6}$$

$$e = 0.0556$$

$$f = 5.9808 \cdot 10^6$$

$$g = 0.6898$$

$$h = -6.4647 \cdot 10^3$$

$$z = 0.5$$

The model is compared with the A123 battery data sheet, resulting in the curves displayed in Fig. 3.20. Three different tests at different temperatures are presented by the manufacturer, where the cycles have been performed with a 100% DoD, and a 2.3 A charge/2.3 A discharge for the 25°C tests (coloured in blue), and 3 A charge/5 A discharge for the 45°C and 60°C tests (coloured in red and black). The capacity fade is displayed as a function of the number of cycles.

Figure 3.20 Capacity fade model validation for an LFP battery. Comparison with the ANR26650M1 manufacturer's data sheet.

The model adjustment to the data provided in the data sheet is considered satisfactory, since there is almost no error for the 25°C case (below 0.3%), less than 1% for the 45°C case, and a maximum of 2.1% for the 60°C case. Nevertheless, an operation temperature of 60°C is relatively close to the maximum operation temperature of the battery, which for the studied A123 battery corresponds to 65°C. Hence, for the majority of industrial applications where the battery temperature remains within a narrow temperature range and close to 23°C-25°C, the model performs with errors below 1%.

A further comparison is performed to validate the capacity fade model for an LFP battery. Petit et.al and Wang et.al used the same A123 ANR26650M1 for developing their semi-empirical capacity fade models for LFP batteries ([110] and [152]). Fig. 3.21

shows the three models comparison for the cases described above, i.e. 100% DoD, and 2.3 A charge/2.3 A discharge for the 25°C curves (coloured in blue), and 3 A charge/5 A discharge for the 45°C and 60°C tests (coloured in red and black). The proposed model performs similar to the models in [110] and [152], and even more accurately in terms of relative error, since Petit et.al and Wang et.al reach a maximum of 1.2% for the 25°C case, lower than 1% for the 45°C case, and 2.3% for the 60°C case.

Figure 3.21 Capacity fade model validation for an LFP battery. Comparison with the capacity fade models published in [110] and [152].

With the two comparisons displayed in 3.21 3.20 the model is considered theoretically validated for an LFP battery.

Capacity fade model validation for an NMC battery

For the NMC chemistry, the SANYO battery model UR18650W is selected. The capacity fade model was parameterized in 3.5 for this specific battery, with the following parameters:

$$a = 1.2918 \cdot 10^{-7}$$

$$b = -7.6878 \cdot 10^{-5}$$

$$c = 0.0114$$

$$d = -6.7149 \cdot 10^{-3}$$

$$e = 2.3467$$

$$f = 154.9601$$

$$g = 0.6898$$

$$h = -2.9467 \cdot 10^3$$

$$z = 0.5$$

The model is compared with the UR18650W battery data sheet, resulting in the curve displayed in Fig. 3.22. The battery data sheet only shows one curve that relates the degradation with the battery use, with 100% DoD cycles at 25°C, a charge current of 0.7 C, and a discharge current of 1 C. The capacity fade is displayed as a function of the number of cycles.

Figure 3.22 Capacity fade model validation for an NMC battery. Comparison with the UR18650W manufacturer's data sheet.

The model shows an accurate adjustment, achieving relative errors up to 3% during the first number of cycles. Nevertheless, as the number of cycles increases, the model tendency approaches to the data sheet curve.

A second NMC battery is selected to complete the validation of the capacity fade model for the NMC chemistry. The Kokam SLPB100255255HR2 battery, used for the electrical model validation is selected. This battery has been selected since it is the Li-ion battery available at Laboratorio de Máquinas Eléctricas at ETSII UPM facilities. The experimental validation of the model, which is described in the next section, is performed

with this battery.

This battery needs to be parameterized in order to validate it. Using the methodology described in 3.5 the model parameters can be obtained. The ageing tests used for parameterizing the selected battery have been obtained from [25]. The obtained parameters are listed as follows:

$$a = 1.3961 \cdot 10^{-7}$$

$$b = -7.7116 \cdot 10^{-5}$$

$$c = 0.0107$$

$$d = -1.2959 \cdot 10^{-3}$$

$$e = 0.4404$$

$$f = 164.7155$$

$$g = 0.6898$$

$$h = -4.2126 \cdot 10^3$$

$$z = 0.5$$

The only information that can be found in this battery data sheet is that, after performing 7000 cycles with a 1C charge and 1C discharge at 25°C and 80% DoD, the remaining capacity is greater than 80%. These cycle specifications were implemented in the model, and the result after 7000 cycles was that the remaining capacity equaled 82.017%, verifying the manufacturer's data.

Considering the data and the model adjustments presented in this section, the model can be considered theoretically validated for both LFP and NMC chemistries.

3.7 Experimental validation

Once the model is theoretically validated, an experimental validation is performed. This section describes the laboratory facility where the ageing tests have been performed, and compares the obtained data with the proposed ageing model estimation.

3.7.1 Laboratory set description

The laboratory facility for performing the experimental validation is located at Laboratorio de Máquinas Eléctricas within ETSII UPM facilities. The installation connects an energy storage system (Li-ion batteries for the works developed in this thesis) to the power grid, and allows for controlling its charge/discharge. It is a bidirectional installation, since the energy is taken from the grid to charge the batteries, and goes back to it during the discharge process. The installation follows the general scheme shown in Fig. 3.23.

Figure 3.23 Scheme of the laboratory installation for performing the experimental validation tests.

The installation accounts for the following elements, starting from the right of the scheme (Fig. 3.23):

- Three-phase 400 V 50 Hz power grid: the complete installation is fed from this connection point.
- Capacitors pre-charge circuit: in order to avoid a sudden current peak absorption from the DC bus capacitors when the installation is powered on, a set of resistors are connected and bypassed after a few seconds.
- Transformer: a 42 kVA transformer allows for lowering the voltage from 400 V to 80 V, which is needed to operate the installation. Moreover, it also works as a galvanic isolator between the batteries and the power grid.

- AC inductive filter: it is located between the transformer and the AC/DC power converter, and allows for connecting two different three-phase systems. The AC/DC inverter outcomes a pulse-based wave, which cannot be directly connected to the transformer sinusoidal three-phase system. The difference between these two three-phase voltages determines the active and reactive power that the installation exchanges with the grid. Three inductors with taps are connected for this purpose, being 1 mH the selected value for the ageing tests.
- AC/DC power converter: bidirectional converter in charge of controlling the DC bus voltage, and the reactive power exchanged with the grid. The applied reference values are 150 V for the DC bus voltage, and 0 kVAr for the reactive power.
- DC bus capacitors: located in the DC bus, the two 6 mF capacitors reduce the ripple in the DC bus voltage.
- DC/DC converter: bidirectional converter that controls the charge/discharge of the energy storage system. It is a DC converter with three legs, so the current is splitted between them. It connects the 150 V DC bus with the energy storage system, whose nominal voltage should not be lower than 30 volts in order to have a reasonable conversion efficiency.
- DC inductive filter: consists of a set of three inductors connected between the output of the DC/DC converter and the energy storage system, and it filters the current that goes in and out of the batteries. Again, three inductors with taps are connected for this purpose, being 1 mH the selected value for the ageing tests.
- Battery pre-charge circuit: connected to the batteries, and in parallel to the rest of the installation, it allows for performing a slow charge of the batteries in case its voltage is so low that the DC/DC converter cannot work properly.
- Energy storage system: 14 cells of the SLPB100255255HR2 model manufactured by Kokam are connected in series. The cell characteristics were previously described in Table 3.7. Hence a 51.8 V rated voltage is obtained.

Except from the energy storage system, the three-phase connection, and the transformer, the remaining elements are distributed inside a cabinet, as seen in Fig. 3.24.

Different energy storage systems, including the Li-ion battery, are placed inside a separate room (Fig. 3.25), which accounts for a heat evacuation system and heater, so the room temperature can be controlled. Besides, a forced air refrigeration system is included facing at the battery, so the cell temperature can be kept within the recommended operation limits.

Figure 3.24 Experimental installation cabinet and control and operation PC.

Figure 3.25 Li-ion battery located at a separate room.

Moreover, different devices are included in the installation for its control and operation:

- Digital Signal Processor (DSP): a microprocessor for processing and generating the IGBTs' trigger signals for both converters is included. A DS1104 from DSpace is internally fed from the control and operation PC, and communicated to it.
- Signal adaptation boards: in order to adapt the IGBTs' trigger signals from the DSP, adaptations boards to convert the ± 5 V signals generated by the DSP into ± 15 V signals for the power converter drivers are required.
- Control and operation PC: the user interface to control and operate the installation consists of a PC equipped with ControlDesk and MATLAB software (Fig. 3.24). Hence, the control is programmed in MATLAB and C code before being compiled and run in the DSP, and the operation is performed through ControlDesk. The interface is shown in Fig. 3.26, and allows for the complete operation of the installation.

Finally, instrumentation equipment is included for measuring voltages, currents, and temperature at different points across the installation. The following devices are installed:

Figure 3.26 Operation interface programmed in the control and operation PC.

- Hall-effect sensors: as seen in Fig. 3.23), different measurements are taken at different points, via hall-effect sensors, which convert 500 V and 300 A signals into 5V signals so the DSP can process them. As seen in Fig. 3.26, hall-effect sensors are included for measuring two AC voltages (U_{rs} and U_{rt}), two AC currents (I_r and I_s), DC bus magnitudes (I_{dc} and U_{dc}), and energy storage system magnitudes (I_{bat} and U_{bat}).
- DC bus counter: complementary to the DC bus hall-effect sensors, a DC counter registers energy, current and voltage at the DC bus.
- Wattmeter: a WT1600 power meter from Yokogawa with precision class 0.1 is included as well. It measures the power and energy during the battery charge and discharge. Moreover, it is also used for correcting the offset of the hall-effect sensors connected to the battery. The wattmeter is shown in Fig. 3.27.
- Thermal sensors: A set of 5 thermal sensors are included and located at different points of the battery, including the positive and negative poles, and three intermediate cells. An extra thermal sensor is connected for measuring the room temperature.

3.7.2 Ageing experimental tests

The described laboratory installation allowed for performing battery ageing tests. However, the installation was not design at first for performing these kind of tests, so there are several considerations regarding the study of battery ageing:

Figure 3.27 Wattmeter connected to the experimental installation.

- Batteries with a high energy need a proper installation to be discharged with high C rates. The described installation, even though it is able to work properly and impose a charge/discharge current command accurately, is not an industrial installation. This implies that the operation thresholds are limited with respect to similar industrial equipment. Despite the included protections, a limitation of 1.5 C charge/discharge has been selected. Hence, the battery cannot be aged with high C rates.
- Given that the installation is not an industrial equipment, it should not be operated without supervision. This implies that only a certain number of cycles per day can be performed, since the installation cannot operate autonomously, and the operators have been working for their corresponding working hours per day. This situation makes the ageing process to be highly extended in time, because the maximum number of hours per day available for performing tests was 8, instead of 24.
- Given that the ageing tests performed with the installation are time consuming, calendar and cycling ageing cannot be dissociated when performing tests. In other words, cycling ageing studies cannot be performed in a few months (which would allow for assuming a negligible calendar ageing contribution), so an inevitable calendar ageing is added in the process.
- Ageing tests make use of dozens of new cells, each one aged under different conditions of C rate, temperature, DoD, etc. The described installation accounts for only one battery, so a single ageing test can be performed.

With these considerations, the following tests have been performed to the battery:

- Cycling tests: 438 cycles with a 60% DoD (between an 80% SoC and a 20% SoC) have been performed. It was not possible to carry out further tests since other works included in this thesis needed to be done. From 21/06/2018 to 19/11/2018,

201 cycles at 0.5C charge (27.5 A) and 1C discharge (55 A) were performed. From 23/11/2018 to 22/03/2019, 237 cycles were performed at 1.5C charge (82.5 A) and 1C discharge. The ambient temperature was kept at $25^{\circ}\text{C} \pm 3^{\circ}\text{C}$.

- Capacity tests: In order to measure the ageing suffered by the battery, a complete capacity test need to be performed after a certain number of cycles. This tests, as defined by the manufacturer, consists of charging up to 100% SoC the battery with a constant current - constant voltage profile (CC-CV), and completely discharge the battery at 0.2C with 23°C , until the cut-off voltage is reached. This tests was performed twice every 50 cycles. The slight variability of the resulted capacity when performing a capacity test, obliged to perform two capacity tests, for repeatability issues.

A voltage variation during a test at 0.5C charge and 1C discharge is shown in Fig. 3.28 as an example. As seen on the image, the tests performance was automatized for speed, so cycles are concatenated.

Figure 3.28 Battery voltage during a test at 0.5C charge and 1C discharge.

Once the experimental data is obtained, the tests are reproduced with the model. The time that the battery has not been under cycling has also been considered, so the calendar ageing can be properly computed. Fig. 3.29 shows the model adjustment to the experimental data obtained from the capacity tests. Moreover, the trend line for the first set of tests, for the second set, and for the whole set of tests is represented.

Figure 3.29 Model adjustment to the experimental data.

As displayed in the figure, important variations between the duplicated capacity tests are obtained, reaching a maximum of 13% variation for the last two capacity tests. Moreover, capacity measurements are not aligned, and some measurements indicate a capacity raise with respect to the previous measurement. This measurements distribution is quite common, as seen in the tests data represented in Section 3.5, and trend lines must be used to obtain the capacity fade tendency. Fig. 3.29 shows the trend line for the first set of tests in blue, and the equivalent line for the second set in green. The total trend line is coloured in red, which is the line that sets the real battery ageing. Comparing the model estimation with this trend line, an accurate adjustment is obtained, with a maximum error below 5%.

This section provides a partial experimental validation of the proposed ageing model for an NMC battery. The limitation in acquiring more cells and the equipment needed to test them, has forced the author of this thesis to parameterize the battery with tests performed by other authors, and to carry out ageing tests that make not possible to differentiate between calendar and cycling ageing. Moreover, the battery has been tested with constant operation parameters, so a variable operation profile, similar to the Artemis and NEDC profiles described in Chapter 2 is needed to fully validate the model against variable charge/discharge conditions. Despite these considerations, the model has been proved to have an accurate performance for low C rates, for working temperatures close to the recommended operation temperature, for a 60% DoD, for two different C rates, and for one and a half year of intense cycling. In most of the cases in industry, these conditions are not far from the real working conditions.

3.8 Final observations regarding LFP and NMC ageing

In order to use the model presented in this thesis, the following studio will try to obtain some conclusions by comparing the two Li-ion studied chemistries. The last section of this chapter is focused on comparing, from a qualitative point of view, the influence of the three main parameters regarding the ageing of LFP and NMC batteries: temperature, C_{rate} , and number of cycles (or Ah flown through the battery). As previously explained, the parameters' influence on the battery ageing varies from LFP to NMC. Even though there are differences between two batteries with the same chemistry, general conclusions can be extracted by comparing two different chemistries.

The two Li-ion cells studied and parameterized in section 3.5 have been selected as representative for LFP and NMC chemistries. A 100% DoD discharge cycle, followed by a charge at 0.2C, and considering one cycle per day have been considered for the analysis. Three different temperatures are considered for each chemistry, presenting the capacity fade evolution as a function of the number of cycles and C_{rate} . Cycling ageing is coloured in blue, calendar ageing in green, and the combination of both, which corresponds to the total battery ageing, in red.

Fig. 3.30, Fig. 3.31, and Fig. 3.32 present the results for the LFP chemistry. The following information can be obtained from them:

- Calendar ageing has a strong dependence on temperature and, as expected, no C_{rate} dependence is observed. After 1000 cycles, a 0.06% of capacity fade is obtained for $T = 0C$, and 2.1% for $T = 50C$.
- Cycling ageing contribution to the total ageing is severely higher than calendar ageing. Moreover, the higher the C_{rate} the higher the degradation. On the other hand, capacity fade increases as the operation temperature drifts away from the recommended operation temperature (25°C). Thus, the capacity fade with $C_{rate} = 1C$ at $T = 25C$ reaches 3.21% after 1000 cycles, while at $T = 0C$ and $T = 50C$ a capacity fade of 3.87% and 5.35% are observed, respectively.

For the NMC chemistry, Fig. 3.33, Fig. 3.34, and Fig. 3.35 present the analogous results as the ones obtained for the LFP cell. The following information can be obtained from them:

- Calendar ageing has, as happened for the LFP chemistry, a strong dependence on temperature and, again, no C_{rate} dependence is observed. After 1000 cycles, a 0.56% of capacity fade is obtained for $T = 0C$, and 3% for $T = 50C$.

Figure 3.30 LFP capacity fade as a function of C_{rate} and number of cycles at $T=0^\circ\text{C}$.

Figure 3.31 LFP capacity fade as a function of C_{rate} and number of cycles at $T=25^\circ\text{C}$.

- The same cycling ageing tendencies observed for the LFP chemistry are observed for NMC. However, the NMC sensitivity to both C_{rate} and temperature is increased.

Figure 3.32 LFP capacity fade as a function of C_{rate} and number of cycles at $T=50^{\circ}\text{C}$.

Thus, after 1000 cycles and at $T = 50^{\circ}\text{C}$, a capacity fade of 01.72% is observed for a $C_{rate} = 1C$, and 21.76% for a $C_{rate} = 5C$. Temperature sensitivity is even higher for NMC chemistries. After 1000 cycles working with $C_{rate} = 1C$, the observed capacity fade equals 0.86% for $T = 25^{\circ}\text{C}$, and 14.29% and 10.72% for $T = 0^{\circ}\text{C}$ and $T = 50^{\circ}\text{C}$, respectively.

The displayed results show a similar tendency for NMC and LFP chemistries, and for both calendar and cycling ageing. Besides, for similar working conditions close to the optimum operation temperature, NMC batteries present a lower capacity fade than LFP. Nevertheless, given that the NMC sensibility to temperature is critical, out of those narrow conditions the battery ageing for NMC batteries exceeds the ageing suffered by LFP batteries.

This analysis allows for confirming some already known considerations regarding batteries, and allow for drawing general conclusions:

- Ageing is closely related to temperature. Li-ion batteries suffer a severe ageing when working out of the recommended operation range, which commonly is set between 28°C and 22°C . Working with low C rates and controlled temperature can drastically extend the battery lifespan. Hence, heat evacuation systems are mandatory for most of industrial applications.

Figure 3.33 NMC capacity fade as a function of C_{rate} and number of cycles at $T=0^{\circ}\text{C}$.

Figure 3.34 NMC capacity fade as a function of C_{rate} and number of cycles at $T=25^{\circ}\text{C}$.

- C rate has also a considerable importance. Given that, in most applications, the C rate cannot always be controlled since it depends on a control that impose a C rate

Figure 3.35 NMC capacity fade as a function of C_{rate} and number of cycles at $T=50^{\circ}\text{C}$.

based on external conditions, the C rate should be precisely controlled whenever the user can. For example, the C rate in an EV battery cannot be controlled during the driving period. However, the charging process must be meticulously selected, and values lower than 1C are recommended.

- As a general recommendation, applications that are not able to have a precise control of the working temperature, should avoid NMC batteries, since operating out of the recommended range implies a huge ageing. On the other hand, LFP batteries suffer less than NMC, allowing for a higher temperature range without experiencing a drastic capacity fade.

3.9 Summary and conclusions

This chapter is focused on developing a Li-ion battery ageing model valid for both LFP and NMC chemistries, on proposing a parametrization methodology, and on validating it both theoretically and experimentally.

First, a general ageing equation has been proposed, relating the capacity fade with the cycling and calendar ageing and with the different variables associated to each of them. Then, the model has been programmed and adapted to variable conditions, and it has been included in a Li-ion battery electrical model.

Moreover, a methodology for parameterizing the ageing model is developed, and two tests matrix with the minimum number of tests needed for the parametrization are proposed. The methodology has been applied to both an LFP and an NMC battery, in order to illustrate how the model can be parameterized.

After that, a theoretical validation of the model by comparing the ageing model estimation with the data provided in an LFP and two NMC batteries data sheets is performed. Relative errors are below 5%. Finally, a partial experimental validation of the model is also carried out, achieving an accurate adjustment of the model for low C rate conditions and temperatures close to the recommended operation temperature.

The chapter finishes with general comments and observations regarding the LFP and NMC battery ageing, enhancing the recommendation of working within the optimum temperature range, and discouraging from implementing NMC batteries if a proper thermal management cannot be applied to the battery.

The developed and validated battery model, including the ageing model, is a useful tool for several actors and sectors, specially for performing a battery system dimensioning process based on technical parameters, without preselecting a LFP or NMC battery. Moreover, optimum operation conditions for existing battery energy storage systems can also be extracted from the model, so the battery can operate as required for each application but maximizing its lifespan. Application developers such as EVs, energy storage integrators into the power grid, battery owners, and other sectors such as renewable energy integration companies, are potential users of the developed model.

According to this, to date December 2020 this model is being used in a collaboration project between the Universidad Politécnica de Madrid and renewable integration companies that want to integrate battery energy storage systems. The model will be parameterized to replicate the behavior of battery containers, and then dimensioning tasks and optimization of the operation will be assessed.

Future works regarding this chapter include expanding and adapting the proposed ageing model to more chemistries among the Li-ion family, complete the experimental validation of the model with tests under variable profiles and higher C rates.

4 | EV Smart Charging Controls for Mitigating Voltage Issues in Low Voltage Networks

4.1 Introduction

This chapter focuses on the electric vehicle (EV) integration into the power grid. Specifically, this chapter analyzes the most relevant EV charging strategies to mitigate voltage unbalance and under-voltage conditions in low-voltage (LV) distribution networks. Besides, a comparison is made between the results obtained with three-phase charging strategies, single-phase charging strategies, and a combination of both. Moreover, a sensitivity analysis via a Montecarlo stochastic evaluation is performed so general conclusions can be extracted.

The objectives of this part of the dissertation are the following:

- Develop and parameterize a LV network model, including household consumptions and EV power demand and charging control.
- Analyze and compare the most relevant strategies for mitigating voltage unbalance and under-voltage conditions with EVs.
- Develop a Montecarlo analysis so conclusions obtained with the LV network can be generalized.
- Develop and compare strategies to mitigate the voltage oscillations induced by the most relevant EVs decentralized smart charging controls.

There are two publications derived from this chapter:

- Journal: J. Nájera, H. Mendonça, R. M. de Castro and J. R. Arribas, "Strategies Comparison for Voltage Unbalance Mitigation in LV Distribution Networks Using EV Chargers," *Electronics*, vol. 8, no. 3, p. 289, 2019.

- Conference: J. Nájera, H. Mendonça, R. M. de Castro and J. R. Arribas, "Strategies for voltage oscillation mitigation in LV distribution networks with EV smart charging control," in *The 25th International Conference and Exhibition on Electricity Distribution (CIRED2019)*, Madrid, Spain, 2019.

4.2 Challenges and possibilities associated to the increased EV penetration into LV networks

Electric vehicles (EVs) are, slowly but undoubtedly, becoming a real alternative to traditional combustion engine cars. In recent years, several European countries have set national electric car deployment targets as a key measure for diminish pollutant and greenhouse gas emissions in urban areas [143]. Financial incentives, together with an increased availability of charging infrastructure and certain benefits when accessing and parking in some urban areas in many cities, are decisive factors for the expected growth of electric vehicle market shares in the following years [67, 28].

Due to this predicted changes in transportation markets, the increasing of EVs penetration in low-voltage (LV) distribution networks is likely to become a challenge for distribution system operators (DSOs), since it can lead to power quality issues. Typical topology for European LV distribution network is three-phase four-wire network, where loads and EVs are not equally distributed across the three phases. The coordinate effect of both EVs and household loads highly contributes to the unbalanced operation of the network, which results in voltage quality concerns such as under-voltage conditions and voltage unbalance [73, 42, 98].

EVs smart charging impact on LV networks power quality has been studied from a wide range of perspectives, including the capability of EVs to mitigate the aforementioned voltage quality concerns. Among the specialized literature, smart charging controls can be divided into centralized and decentralized architectures, whose advantages and disadvantages have been discussed in [47, 147, 126, 32]. Centralized smart charging needs for a central aggregator that controls the charging of all vehicles and optimizes their charging load profiles based on a specific control algorithm. It requires a huge interconnected communication network, so charging profile information can be exchanged between each EV and the aggregator. The centralized architecture allows smoothing the aggregated electric load profile and improves voltage and power quality in a region, but may cause individual vehicles to have voltage peaks in their charging profiles.

On the other hand, the decentralized architecture manages the charging process of

the EVs locally. Decentralized controls present several advantages such as scalability, constant computational effort, and reduced communication requirements [55]. Besides, it allows each individual EV to minimize their respective charging costs, but, collectively, this may not be the optimal solution for the region, since there could be instabilities when all controllers react simultaneously to the measurements. Considering that cost and robustness are similar in both architectures, the decentralized control tends to be a more practical solution, since it is based on local measurements and does not need additional communication infrastructure [32, 80].

In addition to the classification between centralized and decentralized architectures, EV smart charging controls can be divided into those controls suitable for being implemented in a single-phase charger, and those applicable to three-phase chargers. Historically, in European countries the three-phase connection has been reserved for industrial consumers but, in recent years, the number of residential houses with three-phase connection has increased considerably in northern and central Europe [80]. Regarding single-phase connection, EVs smart charging impact on LV networks has been investigated mainly by modulating the active power consumed by the EVs through a droop control [84, 70, 56]. This control highly influences the time needed for a full charge, and could potentially create inconveniences to the user. Besides, the power electronic converter in the charger might introduce a reactive power capability, which can contribute to ancillary services and the correction of voltage issues, such as [99, 121]. Therefore, taking advantage of the hardware available, the reactive power provision has been studied in [85, 79] for a balanced system, and [80] proposes a new control for an unbalanced system based on a droop control.

In relation to three-phase connection, [24] investigates the capability of providing negative and zero sequence in order to diminish voltage unbalance. Moreover, researchs presented in [155, 51] demonstrate that it is possible to achieve substantial improvement in voltage unbalance by balancing the LV network loads. In this case, the strategy also requires a reactive power capability which is always limited by the charger's rated power. Thus, the more active power the charger is dealing with, the lower reactive power is available.

According to this, this chapter comprises three analysis: at first, the most relevant electric vehicle (EV) charging strategies to mitigate voltage unbalance and under-voltage conditions in low-voltage (LV) distribution networks are analysed. Besides, a comparison is made between the results obtained with three-phase charging strategies, single-phase charging strategies, and a combination of both. Secondly, a sensitivity analysis via a Montecarlo evaluation is presented so conclusions obtained with the LV network can be

generalizable. At last, a strategies comparison to mitigate the voltage oscillations induced by the most relevant EVs decentralized smart charging controls is performed.

4.3 Theoretical foundation and regulation for voltage unbalance and voltage level

Any deviation in voltage waveform from perfect sinusoidal, both in terms of magnitude or phase shift, is termed as unbalance. Unbalanced distribution of single-phase loads between the three phases and unequal line impedances imply voltage and current unbalance. As a result, power losses in wires are increased, motors reduce their efficiency severely and suffer degradation, and protection components can trip off [113]. Three-phase voltages can be translated into symmetrical components through the following expression:

$$\begin{bmatrix} \underline{U}_0 \\ \underline{U}_1 \\ \underline{U}_2 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 1 & \underline{a} & \underline{a}^2 \\ 1 & \underline{a}^2 & \underline{a} \end{bmatrix} \begin{bmatrix} \underline{U}_a \\ \underline{U}_b \\ \underline{U}_c \end{bmatrix} \quad (4.1)$$

where

$\underline{a} = e^{j2\pi/3}$ $\underline{U}_a$ $\underline{U}_b$ $\underline{U}_c$ are phase-to-neutral complex voltages

$\underline{U}_0$ $\underline{U}_1$ $\underline{U}_2$ are the zero, positive and negative sequence components respectively

Hence, presence of negative or zero sequence voltages indicate an unbalance operation of the system. European standard EN50160 [140] establishes the voltage characteristics of electricity supplied by public distribution systems. Averaging phase to neutral voltages every 10 min interval over a week, phase-to-neutral voltage magnitudes (U) and Voltage Unbalance Factor (VUF) should remain under the following boundaries for 95% of the time:

- $0.9U_{Nom} < U < 1.1U_{Nom}$
- $VUF < 2\%$

where U_{Nom} corresponds to 1 p.u.

Standard EN50160, as well as other VUF standards, defines VUF as the ratio between voltage negative component and voltage positive component [114]. This definition is sufficient for three-phase three-wire systems, since the absence of neutral wire implies that zero sequence current cannot flow through the system. However, this statement is not valid for three-phase four-wire systems, and VUF definition has to be adapted so

it can take into account the zero sequence contribution. The author of this work has chosen the following VUF definition, previously defined by [15], which is valid for both three-phase three-wire and three-phase four-wire systems:

$$VUF[\%] = \frac{\sqrt{U_2^2 + U_0^2}}{U_1} \times 100 \quad (4.2)$$

Figure 4.1 illustrates the difference between using the formula proposed by EN50160 and the one defined by [15], for the test network described in the following section, with no EVs during 24 hours. It can be seen a severe difference between both curves, where the mean relative error is 2.94%, reaching a maximum error of 5.83%. Hence, for the studies and analysis carried out in this chapter, the author has used the aforementioned improved formula since it is more accurate when measuring VUF and requires a more severe control action for being compliant with the standard.

Figure 4.1 VUF formula comparison.

4.4 Methodology

In order to perform the different analyses proposed in this chapter, a standard LV network has been selected, and proper household and EV consumptions have been modelled.

4.4.1 Test network

The analyzed 50Hz and 400V test network is based on the European Low Voltage Distribution Network Benchmark developed by CIGRE Task Force C6.04 [14]. The original test network is connected to a 20 kV Medium Voltage (MV) network. This MV network is the only feeding point and has a short-circuit power of 100 MVA and X/R ratio equals to 1. Besides, the LV network is divided into three subnetworks: Residential, Industrial and Commercial. Each subnetwork is connected to the MV network through a Dyn1 transformer, whose rated power is 500 kVA for Residential, 150 kVA for Industrial and 300 kVA for Commercial subnetwork. The transformers' secondary star point windings are grounded through a 3 Ω impedance. The MV network of the described test system

is considerably stiff. Due to this situation, power and voltage quality issues that occur in one subnetwork do not influence the other two subnetworks. Hence, since EVs are connected to the Residential subnetwork, disturbances that take place there, only affect the Residential voltage quality. Considering the purpose of this paper, Industrial and Commercial subnetworks are not going to be analyzed further since they are not altered by the different EV charging strategies. The modified network including only the Residential subnetwork is shown in Figure 4.2.

Figure 4.2 Modified CIGRÉ European Low Voltage Distribution Network Benchmark.

The residential test network's consumptions are aggregated in 6 different supply points (R1, R11, R15, R16, R17, and R18). As indicated in Figure 1, Residential subnetwork has its neutral wire grounded every 30 m through a 40Ω impedance. The test network is composed by 17 line segments of the following types:

- Residential main line: Underground NA2XY 4x240 mm²
- Residential ramifications: Underground NA2XY 4x50 mm²

The X/R ratio of each Thévenin's equivalent circuit of the supply nodes in the Residential subnetwork is displayed in Table 4.1. X/R ratio has been calculated using the direct sequence impedance. Accordingly, node R15 can be considered as the weakest point of the network with a significant difference with respect to the rest of supply nodes.

Table 4.1 X/R ratio of each Thévenin's equivalent circuit of supply points.

Node	R11	R15	R16	R17	R18
X/R ratio	0.5366	0.2654	0.5257	0.5199	0.5185

Table 4.2 Household distribution for the test network.

Node	1-ph loads			3-ph loads	Apparent power (kVA)	Power factor
	Ph-a	Ph-b	Ph-c			
R11	0	0	0	1	15	0.95
R15	2	3	3	5	72	0.95
R16	0	0	0	4	55	0.95
R17	0	0	0	1	15	0.95
R18	2	2	2	1	47	0.95

4.4.2 Household consumption

As mentioned before, [14] proposes standard daily power profiles for each subnetwork at transformer level, but lacks of information per individual household. Since that approach does not allow for implementing individual household consumption profiles and individual EV charging profiles, the author has disaggregated the supply points based on a previous version of the test network [105]. Thereby, households are distributed as stated in Table 4.2, having a Residential network with 12 three-phase consumptions and 14 single-phase consumptions. Besides, Table 4.2 shows the apparent power of each supply point, which is divided equally among the consumptions so the maximum power consumed by each supply point does not exceed the indicated apparent power. Moreover, feeder located in R1 is represented as a single aggregated household since there is no data per individual house, and it is characterized by the standard power profile proposed in [14]. It has a rated power of 200 kVA and power factor equal to 0.95.

Power profiles have been obtained for 24 hours at 0.1 seconds basis. Daily individual consumptions for Residential subnetwork are obtained with the software LoadProfileGenerator developed in [112]. The software simulates the behavior of the household occupants based on a desire model, so individual household power profiles can be obtained. Power profiles are randomly generated and are all different, so they have been assigned to individual households randomly. However, apparent power for those power profiles does not necessary coincide with the values of Table 4.2, therefore power profiles' values have been amended by translating them to per unit values and multiplying by the correspondent apparent power.

Due to the lack of information regarding the connection phase of the 14 single-phase

consumptions of the network, they have been divided between phases in an equitable way, i.e., 4 consumptions connected in phase-a, 5 in phase-b and 5 in phase-c. Thus, daily power profile at transformer level is calculated by adding up the power profile of each individual consumption. 24 hours power profile at transformer level for Residential subnetwork is represented in Fig. 4.3, and the Residential subnetwork power profile per phase during the selected time period for simulations in Fig. 4.4. For the purposes of the studies carried out in this chapter, it is sufficient to select a time period of one hour to perform simulations. Time period between 21:00 and 22:00 have been selected, which represents the worst case scenario since household consumptions are close to the peak value, there is a significant unbalance when EVs are not connected, and EVs are likely to have arrived home by 21:00 [48], so there will be an increased power demand due to the EVs charging. The detailed consumption on each load node is shown in Figure 4.5.

Figure 4.3 Daily consumption profile at transformer level for the Residential subnetwork.

Figure 4.4 Residential subnetwork consumption per phase at transformer level for the selected time period.

4.4.3 Electric vehicles

Each household is equipped with an EV with the correspondent EV charger. The EV charging power profile for the base case corresponds to the "dumb-charging" pattern, i.e., the charging starts immediately after the vehicle is connected and consumes 3.68 kW [4]. This charging pattern contributes to the worst case scenario since the power demanded

Figure 4.5 Nodes consumption per phase for the selected time period.

by EVs is not regulated and the penetration rate is 100%.

As aforementioned, the first analysis performed in this chapter aims for comparing single-phase and three-phase charging controls. Therefore, EVs are connected single-phase or three-phase depending on the EV charging controls selected for comparison. For scenarios with single-phase charging controls, vehicles located in households with three-phase consumptions are connected to a random single-phase EV charger with overall equal number of EVs per phase. Besides, vehicles in households with single-phase consumptions are connected to the same phase as the household. On the other hand, for scenarios with three-phase charging controls every EV is connected to a three-phase EV charger. Simulation scenarios are defined in Section 4.6.

4.5 Selected EV charging controls

The most relevant decentralized smart charging controls for improving voltage quality levels in a LV network are the following:

4.5.1 Active power droop control (Droop P)

Droop P control has been mainly investigated for being implemented in single-phase EV chargers. Among the different Droop P controls in the literature, the one proposed in [56] has been selected for the analysis. The charging control takes the EV's phase voltage measurement and calculates the charging power based on the droop P curve shown in Figure 4.6. According to this curve, the charging power is at the maximum value when the phase voltage is above 0.95 p.u. For phase voltages below 0.95 p.u. the charging power

is reduced according to the slope, until it reaches 0.9 p.u. Then, the EV is disconnected as long as the voltage remains low. This strategy presents a straightforward under-voltage regulation.

Figure 4.6 Droop curve of active power control.

The main drawback of the Droop P control is that the time needed for a full charge increases severely, which could be an inconvenience to the EV owner. Thus, the social factor would have an impact to this control strategy, which is beyond the scope of this study. Moreover, since the control does not have information about the two phases where the EV is not connected, there is no possibility of regulating voltage unbalance.

4.5.2 Reactive power droop control (Droop Q)

The Droop Q control selected for comparison and analysis is the control described in [80]. Although it can be implemented in both three-phase and single-phase EV chargers, in this work, it is applied to a single-phase case. Its main advantage with respect to the Droop P control is that it provides under-voltage and over-voltage regulation without compromising the EV full charge. However, this control is incapable of providing voltage unbalance regulation because it only uses single-phase measurements. This control is similar to the Droop P control, but the reactive power is a function of the active power consumed by the EV and the voltage at the EV connection point, $Q = f(P, U)$, as shown in Figure 4.7. In order to not penalize the consumer, the EV charging power is set to the maximum value (1 p.u.). In this way, the control behaves as a voltage droop control, simplified to $Q = f(U)$. Unlike the Droop P control, the Droop Q can be bidirectional, i.e., it can absorb or generate reactive power. For phase voltages from 0.99 p.u. to 0.95 p.u., the control injects reactive power. On the other hand, for voltages between 1.01 p.u. and 1.05, it absorbs reactive power. In addition, there is a dead band for voltages between 0.99 p.u. and 1.01 p.u.

When designing this Droop Q control, it is important to properly size the inverter, so it is capable of providing or absorbing the desired reactive power without affecting the consumed active power. The reactive power limits are assumed to be ± 0.5 p.u. which,

Figure 4.7 Droop curve of reactive power control.

considering that 1 p.u. is equal to the active power consumed by the EV (3.68 kW), equals to ± 1840 var [80].

4.5.3 Load balancing control (LB)

The control proposed in [155] has been implemented in this paper as a LB control. This charging control is designed for being implemented in a three-phase charger, and consists of dividing the EV charging power between the phases based on the phase-to-neutral voltage differences between them. The control behaves as follows:

$$\begin{aligned}
 P_a &= \frac{P_{EV} + k(U_a - U_b) + k(U_a - U_c)}{3} \\
 P_b &= P_a - k(U_a - U_b) \\
 P_c &= P_a - k(U_a - U_c)
 \end{aligned} \tag{4.3}$$

where P_{EV} is the EV charging power, and k is a parameter that controls the inter-phase power delivery.

For the studies carried out in this thesis, a constant value of 100 W/V has been selected for this parameter. Besides, the following equations have to be accomplished in order to satisfy the EV charger size:

$$\begin{aligned}
 P_{EV} &= P_a + P_b + P_c \\
 -P_{EV,max} &\leq P_a + P_b + P_c \leq P_{EV,max}
 \end{aligned} \tag{4.4}$$

where $P_{EV,max} = 3.68$ kW.

This strategy, based on the above equations, has been implemented as shown in Figure 4.8.

Figure 4.8 Load balancing control block diagram.

4.5.4 Sequence compensation control (SC)

The SC control aims for compensating the negative and zero voltage components so VUF equals 0%. The SC control selected is the one proposed in [24], which is suitable for being implemented in three-phase inverters and behaves as follows:

$$\begin{bmatrix} \underline{I}_{B_a} \\ \underline{I}_{B_b} \\ \underline{I}_{B_c} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & \underline{a}^2 & \underline{a} \\ 1 & \underline{a} & \underline{a}^2 \end{bmatrix} \begin{bmatrix} -\underline{I}_{m_0} \\ 0 \\ -\underline{I}_{m_2} \end{bmatrix} \quad (4.5)$$

$$\underline{I}_{abc} = \underline{I}_{B_{abc}} + \underline{I}_{P_{abc}}$$

$$\underline{I}_{P_{abc}} = -\frac{P_{B_{abc}}}{3\overline{E_k}}$$

where $\underline{I}_{abc}$ is the three set of compensating currents, and $\underline{I}_{B_{abc}}$ is the three set of balancing currents that compensate the voltage unbalance originated by the measured currents $\underline{I}_{m_0}$ and $\underline{I}_{m_2}$.

The balancing currents, apart from reducing the VUF, introduce an undesirable active power that needs to be eliminated by injecting a further balanced set of currents $\underline{I}_{P_{abc}}$. This $\underline{I}_{P_{abc}}$ set equals to the active power originated by $\underline{I}_{B_{abc}}$ divided by three times the mean value of the phase voltage magnitudes. The block diagram of this control strategy is shown in Fig. 4.9.

Since this analysis focuses on comparing decentralized control strategies, the measured currents of the above equations correspond to the consumption current of each household.

Figure 4.9 Sequence compensation control block diagram.

4.6 Test case results and discussion

The first study performed in this chapter analyses and compares voltage unbalance and under-voltage conditions for scenarios listed in Table 4.3. Comparing one decentralized single-phase with one decentralized three-phase EV charging control is not appropriate since they do not rely on the same measurements. I.e., single-phase EV chargers can only measure single-phase values and they do not have information about VUF, while three-phase EV chargers have complete information about the three-phases. Hence, comparison are made between uncontrolled single-phase charging, Droop P and Droop Q control, and between uncontrolled three-phase charging, LB and SC control. Moreover, a further comparison is made between scenarios with both types of EV chargers, combining single-phase controls with three-phase controls in the same scenario.

4.6.1 Simulation scenarios

As shown in Table 4.2, the LV test network accounts for 14 households with single-phase connection and 12 with three-phase connection, so there are 26 households with 26 EVs in total. For single-phase EV charging controls scenarios, it is assumed that every household in the test network accounts for a single-phase EV charger, and the correspondent assumption is made for three-phase EV chargers scenarios. For scenarios VII to XI listed in Table 4.3, households with single-phase consumptions are assumed to be equipped with a single-phase EV charger, and those with three-phase consumptions account for a three-phase EV charger.

Simulations have been carried out in the environment of MATLAB Simulink SimPowerSystems. Voltage levels are registered at 0.1 seconds over a time span of 1 hour, and they are presented in box-plots for the supply nodes of the test network (R11, R15, R16, R17 and R18). Furthermore, VUF is calculated averaging its value every 10 min interval, and results are presented for each supply node together with the average VUF for the network. As aforementioned in Table 4.1, R15 is the weakest node of the network, and there are 5 three-phase and 8 single-phase consumptions with the correspondent EVs

Table 4.3 Conducted simulation scenarios.

Scenario	3-phase EV chargers	1-phase EV chargers	EV charging control
I	0	26	No Control
II	0	26	Droop P
III	0	26	Droop Q
IV	26	0	No Control
V	26	0	LB
VI	26	0	SC
VII	12	14	No Control
VIII	12	14	Droop P + LB
IX	12	14	Droop P + SC
X	12	14	Droop Q + LB
XI	12	14	Droop Q + SC

Table 4.4 Number and phase of EVs connected per node for Scenarios I, II and III.

Node	Phase-a	Phase-b	Phase-c	Total per node
R11	0	0	1	1
R15	5	4	4	13
R16	1	2	1	4
R17	0	1	0	1
R18	2	2	3	7
Total per phase	8	9	9	

connected there. Therefore, node R15 is expected to present the lowest voltage levels and the highest VUF.

4.6.2 Scenarios I, II and III: Single-phase controls

Voltage levels and VUF for scenarios I, II and III are represented in Figures 4.10 and 4.11, respectively. Based on phase voltages obtained with uncontrolled charging for Scenario I, phase-b and phase-c remain within the desirable bound during the simulated period. Phase-a voltages at node R15 present values below 0.9 p.u., which is a critical behavior since it is not compliant with the standards. This issue occurs due to the high loading of phase-a during the selected time period (Figure 4.4), in addition to the weakness of node R15, and the high number of EVs connected to that phase, according to Table 4.4.

Droop P and Droop Q control, implemented in scenarios II and III respectively, are decentralized single-phase controls, and they can only provide local voltage regulation for a specific phase at one specific node. Regarding voltage levels, it is observed in Figure 4.10 that both charging strategies contribute to raise phase voltages in the nodes where they

Figure 4.10 Voltage levels for scenarios I, II and III.

are providing regulation and, besides, Droop P control diminishes the voltage variability. The effect of both controls on the rest of the network depends on the network topology and loading profiles, as it would be expected from a decentralized control. As shown in Figure 4.10, Droop P control is providing a significant regulation at node R15 since it is the only node with voltages below 0.95 p.u. Hence, solely voltage levels at that node experience a substantial improvement. On the other hand, the Droop Q control is always active, injecting reactive power in every supply node of the network with EVs connected. Thus, voltage levels in those nodes raise, as seen in Figure 4.10. Summarizing, the higher Droop P regulation, a more substantial improvement is observed in voltage levels, which can be higher than the one obtained with Droop Q control.

Voltage level regulation provided by Droop P control gets voltage levels in the three phases closer due to power curtailment in phases with lowest voltage levels. As a side effect, VUF could be improved. This VUF reduction can be observed in Figure 4.11 at node R15, where VUF presents, after regulation, values significantly lower than the ones obtained in scenario I, which are above the threshold of 2%. As regards to Droop Q control, even though reactive power is injected in every phase, this contribution is not taking into account the voltage level of the three phases, so it is unable to diminish VUF.

4.6.3 Scenarios IV, V and VI: Three-phase controls

Results for scenarios IV and V are presented in Figures 4.12 and 4.13. As happened for the single-phase controls comparison, phase-b and phase-c voltages obtained with uncontrolled charging for scenario IV remain within the desirable limits during the simulated period, while phase-a voltages at node R15 reach values below the minimum threshold. Apart from that phase voltage, the remaining voltages of the network do not present under-voltage condition.

Both LB and SC control are three-phase decentralized controls, and they aim to mit-

Figure 4.11 VUF for scenarios I, II and III.

Figure 4.12 Voltage levels for scenarios IV, V and VI.

igate VUF. Results displayed in Figure 4.12 show that the VUF reduction achieved with the two charging controls is noticeably high, and similar for both controls. LB control mitigates VUF by balancing the active power between the three phases of each node, while SC control eliminates the negative and zero components of the household consumption current by injecting/absorbing reactive power. Hence, neither of both controls provide voltage level regulation, as it is shown in Figure 4.13. If desired, this voltage levels regulation can be implemented in LB control through reactive power control, which has not been used for the scenarios analysed in this paper. However, this voltage level regulation cannot be implemented in SC control since reactive power regulation is already compromised for VUF mitigation.

4.6.4 Scenarios VII, VIII, IX, X and XI: Combined controls

Simulation results for Scenarios VII, VIII, IX, X and XI are presented in Figures 4.14 and 4.15. Scenario VII, uncontrolled charging, is considerably different with respect to the previous uncontrolled charging scenarios I and IV. In Table 4.5, it is observed that

Figure 4.13 VUF for scenarios IV, V and VI.

Table 4.5 Number and phase of EVs connected per node for Scenarios VII, VIII, IX, X and XI.

Node	Phase-a	Phase-b	Phase-c	3-Phase	Total per node
R11	0	0	0	1	1
R15	2	3	3	5	13
R16	0	0	0	4	4
R17	0	0	0	1	1
R18	2	2	2	1	7
Total per phase	4	5	5	12	

phase-b and phase-c are more loaded in Scenario VII than phase-a at node R15. Hence, phase-c at node R15 presents voltages below 0.9 p.u. for uncontrolled charging, while phase-a and phase-b are close to that threshold.

Figure 4.14 Voltage levels for scenarios VII, VIII, IX, X and XI.

When combining both three-phase with single-phase decentralized controls, three-phase EV chargers aim for VUF regulation while single-phase EV chargers are focused

on voltage-level regulation. Regarding voltage levels, conclusion drawn from section 4.6.2 (scenarios II and III) can be applied to scenarios VIII to XI. As seen in Figure 4.14, Droop P control is significantly effective in nodes where it regulates the EVs charging power, while Droop Q control increases voltage levels in every node.

Figure 4.15 VUF for scenarios VII, VIII, IX, X and XI.

The aforementioned side effect of Droop P control combined with the VUF regulation of LB and SC controls, achieve a huge VUF reduction. On the other hand, as Droop Q control is not able to contribute to VUF mitigation, the combination with LB and SC controls are less effective. The different results between scenarios VIII and IX (Droop P-LB and Droop P-SC) and scenarios X and XI (Droop Q-LB and Droop Q-SC) are due to the three-phase control regulation. SC control eliminates the negative and zero sequence components of the consumption current of the household where it is implemented. Since there is a combination of three-phase and single-phase consumptions at nodes R15 and R18 (Table 4.2), SC control is unable to mitigate the node's VUF because it does not have influence in single-phase households. On the contrary, since every household connected at each node measures the same phase voltages, LB control can compensate the single-phase controls effect and contribute to the VUF mitigation. In summary, in presence of single-phase charging controls, SC control is observed to be inadequate to reduce VUF. The most relevant results are summarized in Table 4.6, where $U_{min_{R15}}$ is the minimum voltage at node R15 on the most loaded phase, $U_{mean_{R15}}$ is the mean voltage at node R15 on the most loaded phase, and VUF_{max} is the maximum VUF.

4.7 Montecarlo analysis methodology

Conclusions obtained from the previous analysis are not fully generalizable. Performance tendencies can be extracted, but the real behavior of a LV grid with EVs accounts for

Table 4.6 Summarized results for the conducted scenarios.

Scenario	EV charging control	$U_{min_{R15}}(p.u.)$	$U_{mean_{R15}}(p.u.)$	$VUF_{max}(\%)$
I	No Control	0.872	0.898	3.707
II	Droop P	0.911	0.931	0.865
III	Droop Q	0.882	0.908	3.384
IV	No Control	0.886	0.912	2.561
V	LB	0.907	0.919	0.753
VI	SC	0.909	0.917	0.554
VII	No Control	0.895	0.919	2.373
VIII	Droop P + LB	0.919	0.931	0.727
IX	Droop P + SC	0.917	0.932	0.799
X	Droop Q + LB	0.912	0.927	1.248
XI	Droop Q + SC	0.907	0.929	2.116

several uncertainties, such as EV penetration, EV connection node, EV connection phase, and EV charging control, among others. For investigating the uncertainty effects on the VUF and voltage level of the previously defined network, a Montecarlo based stochastic evaluation is performed. The flow chart is shown in Fig. 4.16.

The considered uncertainties include EV penetration, EV connection node, EV connection phase, and EV charging control:

- EV penetration: three penetration levels for setting the number of EVs connected to the grid are considered: 30% (8 EVs), 65% (17 EVs), and 100% (26 EVs).
- EV connection node: all connection nodes are considered, i.e. R11, R15, R16, R17, and R18.
- EV connection phase: EVs accounting for a single-phase charging control can be connected either to phase a, b, or c.
- EV charging control: the four charging controls described for the previous analysis (Droop P, Droop Q, LB. and SC), plus the uncontrolled charge (dumb charging pattern) are selected.

For each uncertainty, equal probability has been selected for the different setting options, i.e. for the case of EV penetration, an equal probability of 33.3% is assumed for 30%, 65%, or 100% EV penetration.

The stopping rule of the Montecarlo method has been chosen based on achieving an acceptable convergence for VUF and voltage level which, as explained in [154], can be achieved with a number of trials equal to $N = 10.000$.

Figure 4.16 Flow diagram for the performed Montecarlo analysis.

4.8 Montecarlo analysis results and discussion

The sensitivity analysis is performed by analyzing individually the effect of each uncertainty (univariate analysis), and considering the combination effect of two variables (bivariate analysis).

4.8.1 Statistical variables

Given the considered uncertainties, the results obtained from the Montecarlo analysis are analyzed based on the following variables:

- EV penetration: as defined previously, results are analyzed for every value of EV penetration.
- EV connection node: as defined previously, results are analyzed for all connection nodes.
- Predominant control: a control is considered predominant if its implementation exceeds the second most implemented control by at least a 30%.
- Phase similarity: three cases are considered for phase similarity, depending the consumption power (load and EVs) that each phase is dealing with: a similar phase consumption is considered when there is a difference lower than 30% between phases;

intermediate similarity is considered when there is one phase that exceeds that 30% of similarity; at last, dissimilar phase consumption is considered when there are differences above 30% between the three phases.

The mean value obtained for the whole Montecarlo simulations is taken when representing the results in the following sections.

4.8.2 Univariate analysis

The univariate results for the sensitivity analysis are presented as follows, relating voltage level and VUF to the statistical variables afore defined, and once the whole Montecarlo results have been processed.

VUF and voltage as a function of the connection node

VUF and voltage relation to the EV connection node is presented in Fig. 4.17. As previously mentioned, node R15 is the most loaded node and also accounts for the lowest X/R ratio. Hence, as happened for the previous analysis, it is again the weakest point of the grid. As expected, highest VUFs occur at node R15, while the rest of the nodes remain below the 2% limit. The VUF grows for the nodes located further from the transformer. On the other hand, mean voltages during the studied period vary according to the X/R ratio of the nodes, being the lowest the node R15, with a significant difference.

Figure 4.17 VUF and voltage as a function of the EV connection node.

VUF and voltage as a function of the EV penetration

VUF and voltage relation to EV penetration are presented in Fig. 4.18. The relation is straightforward, since increasing the number of EVs connected to the grid increases the VUF and decreases the mean voltage. No overall VUF threshold violation is achieved for 100% EV penetration.

Figure 4.18 VUF and voltage as a function of the EV penetration.

VUF and voltage as a function of the phase similarity

VUF and voltage relation to the phase similarity are presented in Fig. 4.19. The VUF variation behaves as expected, since dissimilar phases account for higher VUFs. Voltage tendency is also easily explained, given that simulations with dissimilar phases tend to correlate with a high number of EVs connected to the grid, since the power consumed by the EVs is also taken into consideration when defining phase similarity. Hence, from a general perspective, simulations with higher consumptions account for lower voltages.

Figure 4.19 VUF and voltage as a function of the phase similarity.

VUF and voltage as a function of the predominant control

VUF and voltage relation to the predominant control are presented in Fig. 4.20. Conclusions obtain from this analysis are aligned with the ones obtained from the analysis performed in section 4.6. LB control allows for the highest VUF reduction, being the Droop Q control the one that perform worst. SC control, as previously explained, does

not combine properly with other charging controls. According to voltages, single-phase controls perform best, given that Droop Q provides reactive power, and Droop P control forces a charging power curtailment that helps in rising voltage levels. The two three-phase controls are focused on VUF reduction, so no direct benefits are expected from the point of view of the voltage level.

Figure 4.20 VUF and voltage as a function of the predominant control.

4.8.3 Bivariate analysis

The bivariate results for the sensitivity analysis are presented as follows, relating voltage level and VUF to the combination of two variables, and once the whole Montecarlo results have been processed.

VUF and voltage as a function of the connection node and EV penetration

VUF and voltage relation to the connection node and EV penetration are presented in Fig. 4.21. The VUF and voltage variation as a function of the EV connection node and EV penetration is as expected. Increasing the number of EVs connected to the grid causes a VUF increment and an overall voltage level reduction. As seen in Fig. 4.21, the mean VUF value exceeds the 2% threshold for EV penetrations of 65% and 100%. It must be noted that the voltage figure at Fig. 4.21 presents node R15 at first, while the VUF figure presents it at last. This modification has been applied in order to have a better visualization of the results.

VUF and voltage as a function of the connection node and phase similarity

VUF and voltage relation to the connection node and phase similarity are presented in Fig. 4.22. Another straightforward relation is found for this case, where dissimilar phases account for higher VUFs, and node R15 presents the highest VUF and the lowest voltages.

Figure 4.21 VUF and voltage as a function of the connection node and EV penetration.

Figure 4.22 VUF and voltage as a function of the connection node and phase consumption similarity.

VUF and voltage as a function of the connection node and predominant control

VUF and voltage relation to the connection node and predominant control are presented in Fig. 4.23. As happened in the univariate analysis, the expected behavior is replicated, where LB control provides the greatest VUF reduction, and node R15 presents critical values for VUF, and low voltage values for every predominant control.

VUF and voltage as a function of the EV penetration and predominant control

VUF and voltage relation to the EV penetration and predominant control are presented in Fig. 4.24. With a 100% of EV penetration, results are aligned with the rest of the results related to predominant controls. However, for lower levels of EV penetration, there is no important VUF variation, and similar VUF levels are obtained for all control cases. This is an important conclusion, since indicates that high levels of EV penetration are required to observe a VUF benefit from the EV charging control, and decentralized controls are not able to provide an overall VUF regulation if they are not implemented massively.

Figure 4.23 VUF and voltage as a function of the connection node and predominant control.

Similarly, voltage levels follow the expected behavior for 100% EV penetration, and lower percentages are not relevant for improving the overall voltage level.

Figure 4.24 VUF and voltage as a function of the number of EVs and predominant control.

VUF and voltage as a function of the EV penetration and phase similarity

VUF and voltage relation to the EV penetration and phase similarity are presented in Fig. 4.25. Comparable to the previous case, the expected VUF and voltage behavior is obtained for a 100% of EV penetration. However, there are slight VUF variations for all 9 combinations of number of EVs and phase similarity, so no direct relationship can be established. A similar situation occurs for voltage levels, presenting the lowest voltage for similar phases and 30% of EV penetration. Again, no direct relationship can be established.

Figure 4.25 VUF and voltage as a function of the number of EVs and phase consumption similarity.

VUF and voltage as a function of the phase similarity and predominant control

VUF and voltage relation to the phase similarity and predominant control are presented in Fig. 4.26. Both figures illustrate that the highest influence of the EV charging control is achieved with dissimilar phases. In this sense, the highest VUF reduction is obtained for LB control and dissimilar phases, and the highest voltage level for Droop Q control and dissimilar phases, where the reactive power provision in the most loaded phases is expected to be greater.

Figure 4.26 VUF and voltage as a function of the phase consumption similarity and predominant control.

4.8.4 Sensitivity analysis summary

A qualitative sensitivity analysis can be assessed based on the results obtained along sections 4.8.1, 4.8.2, and 4.8.3. Given that voltage issues have a local effect, a stochastic analysis aggregating the results for a set of nodes does not give information about the

accuracy and the convenience of using smart charging controls for regulating VUF and voltage. However, a different analysis can be performed, which includes a qualitatively assessment of the importance of different grid variables. In this thesis, the selected variables are EV penetration, phase consumption similarity, and predominant control.

At first, Montecarlo results (VUF and voltage) accounting for connection node dependency validate the tendency obtained for the specific case analysis developed in Section 4.6. Nodes with a higher loading condition and located further from the generator present the highest VUF and the lowest voltage levels, as expected.

The VUF and V dependency on EV penetration gives the following conclusions:

- The higher the EV penetration, the higher the overall VUF and the lower the mean voltage level.
- Correcting unacceptable VUF or voltage levels with smart charging controls may not be an appropriate solution if there is not a high EV penetration. Specifically, and given the local condition of voltage issues, high penetration of EVs is required at or nearby the problematic nodes, since a low EV penetration might not be sufficient for providing the required regulation.
- No direct relationship can be established with phase consumption similarity.

The results dependency on the most predominant control arise the following conclusions:

- LB and Droop P controls help to reduce the VUF due to the reasons detailed in Section 4.6, while Droop Q control helps in improving voltage levels. SC control remains as an inappropriate solution when combined with other controls.
- LB control has a major influence on the VUF reduction when there is a dissimilar phase consumption, given that consumption situation is related with higher VUF.
- Droop Q control has a major influence on the voltage level when there is a dissimilar phase consumption. For the selected grid and selected load configuration, a dissimilar phase consumption situation usually implies that one phase accounts for the majority of the EVs and, hence, higher consumption.

Finally, conclusions from phase consumption similarity dependency have already been indicated in relation to the rest of the variables:

- Dissimilar consumptions are closely related with a higher overall VUF.

- A dissimilar phase consumption situation usually implies that the EVs are mostly connected at the same phase, reducing severely the voltages on that phase and, consequently, the overall voltage level of the grid.

4.9 Strategies for voltage oscillation mitigation when implementing EV smart charging controls

4.9.1 Instability when dealing with decentralized controls

Along this chapter, four decentralized controls for mitigating VUF and improving voltage levels have been analyzed. As previously explained, decentralized controls tend to be considered a more practical architecture, since they are based on local measurements and do not need additional communication infrastructure [32].

However, decentralized controls that rely on local voltage measurements may present instabilities when all controllers react simultaneously to a certain event. Namely, since each control acts at the same time and there is no communication between controls, the correction action of each control is unable to reach a stable behaviour because the set point of the control is constantly changing. Consequently, the network suffers from voltage oscillations that should be diminished and eliminated for a reliable operation.

This section develops, analyses and compare different strategies to mitigate the voltage oscillations that the four EV decentralized smart charging controls introduce in the LV network under study.

4.9.2 Strategies for voltage oscillation mitigation

Three strategies are developed and described in this section: random delay strategy, hysteresis comparison strategy, and sample time strategy.

Random delay strategy

The random delay strategy consists of implementing a small delay to the voltage level that each control is measuring. This delay should be different for each EV charging control, so a random number should be given to each delay. By doing this, EVs charging controls act simultaneously but their correcting action is based on different voltage measurements, since some of them are delayed. Thus, the controls are decoupled and voltage oscillations can be reduced or, depending on the charging control and the network structure, eliminated.

Hysteresis comparison

Hysteresis comparison strategy works in a similar way as a Schmitt trigger. Fig. 4.27 illustrates this behaviour when applied to the active power droop control. If voltage decreases from values above 0.9 p.u. the droop control follows the blue line, and if voltage grows from values below 0.92 p.u., it follows the red line. Voltage limits of 0.9 and 0.92 can be set to a different value for other applications or controls.

Figure 4.27 Hysteresis comparison behavior.

This strategy keeps the charging power at the minimum value until voltage reaches the higher voltage threshold of 0.93 p.u. Hence, it can eliminate voltage oscillations, preventing for charging power regulation when voltages are within the dead band (0.91 p.u. - 0.93 p.u.).

Sample time strategy

The sample time strategy consists of sampling the voltage with a different step time for each control. In this way, each control sets its correcting action based on a fixed voltage until the voltage is sampled again. The sample time strategy, as happened with random delay strategy, decouples the control of different EV chargers connected to the LV grid. The difference is that with sample time strategy the controls do not react simultaneously, since each one of them change its set point on a different time instant.

4.9.3 Strategies comparison results

In order to analyse the different strategies when mitigating voltage oscillation, simulations have been carried out for the three controls that rely on voltage measurements, i.e. Droop P, Droop Q, and LB charging control. Three scenarios are defined, one with each

EV charging control, where they are implemented in each household of the test network. Besides, voltage mitigation strategies are as well implemented together with the controls in each scenario, so different cases are compared. Hysteresis comparison strategy is only considered for active power droop control scenario since it cannot be applied to the rest of scenarios.

Simulations have been carried out in the environment of MATLAB Simulink SimPowerSystems, and voltage levels have been registered every 0.1 seconds over a time span of 1 hour. Results show phase-a voltage evolution during the simulation time for node R15. Voltages for other phases and nodes present different levels than phase-a voltage at node R15, but the amplitude of voltage oscillations is similar for every phase and node. Hence, it is sufficient to present the results for one phase at one node in order to compare and analyse the different strategies for mitigating voltage oscillation.

Droop P scenario

The three strategies for mitigating voltage oscillations are compared in this scenario, together with the active power droop control. As seen in Fig. 4.28, all three strategies manage to diminish the amplitude of voltage oscillations, although only the sample time strategy eliminates it completely. Hysteresis comparison (or relay comparison) strategy is unable to eliminate the voltage oscillation because the amplitude is higher than its dead band (Fig. 4.27). On the other hand, random delay strategy improves the hysteresis performance during the first half of the simulation, but the amplitude of the oscillations increases at the end of it.

Figure 4.28 Mitigation strategies for voltage oscillations with Droop P control.

Droop Q scenario

Fig. 4.29 shows the random delay and sample time strategies behaviour for the second scenario, where Droop Q control is implemented. Results show that both strategies are able to eliminate entirely the voltage oscillations. As seen in Fig. 4.29, voltage profiles for random delay and sample time strategies are considerably different, i.e., the voltage difference between the two profiles reach values close to 0.25 p.u. during the simulation. The control action of the sample time strategy is based on a sampled voltage measurement, which may be distant from the real voltage value during the period between two samples. When the EVs penetration is high the voltage difference may vary significantly, as happen in this scenario. Hence, it is important to set a short step time between two samples, so the control is able to react fast to voltage quality events while reducing voltage oscillations.

Figure 4.29 Mitigation strategies for voltage oscillations with Droop Q control.

Load Balancing scenario

Fig. 4.30 shows the random delay and sample time strategies behaviour for the third scenario, where load balancing control is implemented. Results show that both strategies are able to diminish considerably the amplitude of voltage oscillations, and sample time strategy is able to eliminate it entirely. As happened in the first scenario, random delay strategy has a good behaviour at the beginning of the simulation but loses reliability at the end. In this scenario, the difference between both strategies' voltage profiles is less noticeable than in the second scenario, although it is difficult to make a comparison between both voltages due to the oscillations in the voltage profile of the random delay strategy.

Figure 4.30 Mitigation strategies for voltage oscillations with LB control.

4.10 Conclusions

EVs increased penetration will likely have a great impact in low-voltage (LV) distribution networks, since it leads to power and voltage quality concerns. In order to mitigate the undesirable effects originated by uncontrolled EV charging, several decentralized smart charging controls have been proposed in the recent years, both for three-phase and single-phase EV chargers. Trying to clarify which of the different solutions acts in a better way regarding a specific objective, this chapter presents a first analysis that compares four of the most relevant smart charging controls, with the aim of reducing the VUF and avoiding under-voltage conditions. The selected controls are active power droop control (Droop P) and reactive power droop control (Droop Q) for single-phase EV chargers, and load balancing control (LB) and sequence compensation control (SC) for three-phase EV chargers. Comparisons and analyses were made between the two single-phase controls, between the two three-phase controls, and between a combination of Droop P-LB, Droop P-SC, Droop Q-LB and Droop Q-SC controls. The selected controls were tested on a standardized European Low Voltage Distribution Network developed by CIGRE for the worst case scenario, i.e., 100% EV penetration during a highly loaded and unbalanced time period.

Single-phase controls provide phase voltage regulation, since they are not able to mitigate VUF due to the lack of information about the three phases. On the other hand, three-phase controls aim to mitigate VUF, but they do not provide voltage level regulation. Out of the results, it is concluded that Droop P control provides a huge voltage level raise and reduces the voltage variability, although it only acts on nodes with low

voltages. Furthermore, as a side effect, Droop P control balance the phase voltages and is able to reduce VUF. On the other hand, Droop Q control influence on voltage levels is not as noticeable as Droop P control, but it affects every node.

Regarding three-phase controls, both LB and SC controls are able to reduce VUF when every EV charger is equipped with the same charging control. Nevertheless, SC control loses effectiveness when combined with single-phase charging controls, while LB control is able to contribute to VUF mitigation in that situation.

In conclusion, Droop P and LB controls have been proved to be the most suitable solution for DSOs when dealing with under-voltages, due to the high improvement in voltage level at critical nodes provided by Droop P control, and the better association and contribution to VUF mitigation provided by LB control with respect to SC control. If the network experiences over-voltages, Droop P control is unable to regulate voltage levels in order to be compliant with the standards. However, Droop Q control is able to regulate both over and under voltages due to its versatility. Hence, the control strategies selected by the DSO should take into consideration the aforementioned issues.

A second analysis has been performed, considering the standardized European Low Voltage Distribution Network, and the four selected decentralized controls. A sensitivity analysis via a Montecarlo stochastic evaluation is performed, so general conclusions can be extracted. Despite the local effect of voltage issues such as high VUF and low voltages voltage, some trends can be obtained for the following variables: EV penetration, phase consumption similarity, and predominant control. The results obtained in the previous analysis have been reaffirmed, and Montecarlo results indicate that succeeding in regulating voltage issues may require a high EV penetration, at least nearby the problematic nodes. Moreover, dissimilar phase consumption scenarios get the highest benefit from the LB control according to VUF mitigation, and also from the Q control regarding voltage level assessment. Finally, no direct relationship has been observed between EV penetration and phase consumption similarity.

A third analysis is performed, considering different strategies to mitigate voltage oscillations. Decentralized charging controls induce voltage oscillations in the network when they react simultaneously, so strategies for mitigating voltage oscillations have been proposed in this paper. Three strategies have been selected: random delay, hysteresis comparison, and sample time strategy. These strategies have been applied to the three selected controls that are based on local voltage measurements, proving that even the simplest strategy can diminish the amplitude of voltage oscillations. Moreover, sample time strategy is able to eliminate entirely the voltage oscillations. According to the rest of strategies,

their effectiveness depends on the charging control and the LV network where they are implemented.

5 | Conclusions and future work

The work described in this document is focused on Li-ion battery ageing. This aspect has been studied for electric transportation applications. The two first parts of the thesis were developed thinking on the application designer and electric transport manufacturer, while the latter is focused on the battery owner and the power grid.

Conclusions corresponding to each of the chapters have been included in the corresponding sections at the end of them, so they will not be repeated here. Given that those conclusions were specific, this chapter presents a more general perspective and thoughts of the studied topic. However, conclusions drawn for the individual chapters are more representative of the work developed during this thesis than the ones included at follows.

Designing a HESS for electric transportation formed by Li-ion batteries and SCs is not straightforward. It commonly requires an optimization process which leads to a compromised solution. A techno-economical analysis is usually demanded and, from the point of view of the Li-ion battery ageing, what is best for the economical aspect and for the rest of technical variables may not be optimal for the battery capacity fade. Given the variables that influence the battery ageing, the HESS control strategy has a critical importance when imposing a certain working condition to the battery. The main contributions from this part of the thesis are the development of an on-line capacity fade model for Li-ion batteries, and the development of a dimensioning methodology for a hybrid energy storage system with batteries and supercapacitors. Besides, an application case for an electric bus is provided where the developed methodology is implemented.

From an industrial point of view, equivalent-circuit models allow for simplicity and versatility, while keeping a high degree of accuracy. Dimensioning or optimization processes that are already based on a specific battery chemistry may obtain benefits from more complex and precise models, but a great number of studies that aim for general trends without deciding a specific chemistry or technology can find equivalent-circuit models specially useful. In this sense, semi-empirical ageing models for Li-ion batteries aim for this simplicity and versatility. Developing a Li-ion battery ageing model representative of the majority of chemistries among Li-ion family would be highly beneficial

for the designing process of several devices and transports. However, it is not a simple task, and including different chemistries might increase the complexity of the model (the number of parameters). Again, a compromise solution is required, so the parametrization process can be developed with a few number of tests and the model is valid for as much chemistries as possible. The main contributions from this part of the thesis are the development and validation of a capacity fade model valid for both LFP and NMC chemistries, and a methodology for parameterizing it. The model has been developed theoretically and via experimental tests in laboratory with a representative battery of 3kWh.

Smart charging control implementation for EVs in order to provide some kind of service to the electric grid, may be closer in time than we think. In that projected scenario, smart charging controls are likely to be decentralized, so only the ones able to "collaborate" with other decentralized controls implemented in other power converters without causing disturbances should be selected. Moreover, regarding Li-ion batteries, those services may not be beneficial for their lifespan, so compensation measurements should be applied to the battery owner, or specialized power converters that prevent for a fast ageing should be implemented. The main contributions from this part of the thesis are the analysis of the influence of smart charging controls for electric vehicles in the grid parameters, and development of a Montecarlo analysis so conclusions can be generalizable.

In this thesis, Li-ion battery ageing has been studied from three different perspectives, and some interesting conclusions have been drawn in the corresponding chapters. Nevertheless, the different contributions can be further developed and improved. The author of this thesis plans to assess some of them personally in the following years, but there is a lot of room for other researchers to evaluate them.

Regarding Chapter 2, the developed dimensioning methodology that considered energy efficiency and battery ageing, should be completed with a final translation into economical terms. This techno-economic analysis would then be helpful for HESS designers in order to select a final solution of HESS topology and control, depending on the driving cycle. Moreover, few HESS topologies, control strategies, and driving cycles have been studied, and the methodology could be extended to a wider range of electric transports.

Conclusions drawn in Chapter 3 have also room for improvement. At first, the experimental validation of the capacity fade model is not completed, and higher C rates and variable charge/discharge profiles are needed to fully validate it. Moreover, internal resistance ageing has not been included, although the limiting variable for Li-ion batteries is usually the capacity. However, its inclusion for LFP and NMC chemistries would extend the number of applications where the proposed ageing model can be useful. At last, the de-

veloped model could be applied and adapted to other chemistries among the Li-ion family.

Finally, Chapter 4 could also advance further in the conclusions by including smart charging controls for ancillary services that involve active power provision (for frequency events, for example). Moreover, a capacitive filter design methodology could be developed so the reactive power provision by the power converter reduces its effects on the battery ageing, including an economic evaluation so a techno-economic decision can be performed.

Bibliography

- [1] Victor Agubra and Jeffrey Fergus. “Lithium ion battery anode aging mechanisms”. In: *Materials* 6.4 (2013), pp. 1310–1325.
- [2] AL Allègre, R Trigui, and A Bouscayrol. “Different energy management strategies of Hybrid Energy Storage System (HESS) using batteries and supercapacitors for vehicular applications”. In: *2010 IEEE Vehicle Power and Propulsion Conference*. IEEE. 2010, pp. 1–6.
- [3] Srikanth Allu et al. “A generalized multi-dimensional mathematical model for charging and discharging processes in a supercapacitor”. In: *Journal of Power Sources* 256 (2014), pp. 369–382.
- [4] Monica Alonso et al. “Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms”. In: *Energies* 7.4 (2014), pp. 2449–2475.
- [5] Parisa Amiribavandpour, Weixiang Shen, and Ajay Kapoor. “Development of thermal-electrochemical model for lithium ion 18650 battery packs in electric vehicles”. In: *2013 IEEE Vehicle Power and Propulsion Conference (VPPC)*. IEEE. 2013, pp. 1–5.
- [6] Zahra Amjadi and Sheldon S Williamson. “A novel control technique for a switched-capacitor-converter-based hybrid electric vehicle energy storage system”. In: *IEEE transactions on industrial electronics* 57.3 (2009), pp. 926–934.
- [7] Michel André. “The ARTEMIS European driving cycles for measuring car pollutant emissions”. In: *Science of the total Environment* 334 (2004), pp. 73–84.
- [8] Eliana Arango et al. “Asymmetrical interleaved DC/DC switching converters for photovoltaic and fuel cell applications—Part 1: Circuit generation, analysis and design”. In: *Energies* 5.11 (2012), pp. 4590–4623.
- [9] Pankaj Arora, Ralph E White, and Marc Doyle. “Capacity fade mechanisms and side reactions in lithium-ion batteries”. In: *Journal of the Electrochemical Society* 145.10 (1998), p. 3647.
- [10] D Aurbach et al. “On the correlation between surface chemistry and performance of graphite negative electrodes for Li ion batteries”. In: *Electrochimica acta* 45.1-2 (1999), pp. 67–86.

- [11] Doron Aurbach. “Review of selected electrode–solution interactions which determine the performance of Li and Li ion batteries”. In: *Journal of Power Sources* 89.2 (2000), pp. 206–218.
- [12] Issam Baghdadi et al. “Lithium battery aging model based on Dakin’s degradation approach”. In: *Journal of Power Sources* 325 (2016), pp. 273–285.
- [13] Anthony Barré et al. “A review on lithium-ion battery ageing mechanisms and estimations for automotive applications”. In: *Journal of Power Sources* 241 (2013), pp. 680–689.
- [14] Stefano Barsali et al. *Benchmark systems for network integration of renewable and distributed energy resources*. 2014.
- [15] M Tavakoli Bina and A Kashefi. “Three-phase unbalance of distribution systems: Complementary analysis and experimental case study”. In: *International Journal of Electrical Power & Energy Systems* 33.4 (2011), pp. 817–826.
- [16] Henrik Bindner et al. *Lifetime modelling of lead acid batteries*. Vol. 12. 2005.
- [17] Christoph R Birkel et al. “Degradation diagnostics for lithium ion cells”. In: *Journal of Power Sources* 341 (2017), pp. 373–386.
- [18] Holger Blanke et al. “Impedance measurements on lead–acid batteries for state-of-charge, state-of-health and cranking capability prognosis in electric and hybrid electric vehicles”. In: *Journal of power Sources* 144.2 (2005), pp. 418–425.
- [19] Pierre Clément Bland. “Développement d’un modèle de simulation de supercondensateur et validation expérimentale”. PhD thesis. École de technologie supérieure, 2012.
- [20] Ira Bloom et al. “An accelerated calendar and cycle life study of Li-ion cells”. In: *Journal of Power Sources* 101.2 (2001), pp. 238–247.
- [21] Michel Broussely et al. “Main aging mechanisms in Li ion batteries”. In: *Journal of power sources* 146.1-2 (2005), pp. 90–96.
- [22] Long Cai and Ralph E White. “Mathematical modeling of a lithium ion battery with thermal effects in COMSOL Inc. Multiphysics (MP) software”. In: *Journal of Power Sources* 196.14 (2011), pp. 5985–5989.
- [23] Long Cai and Ralph E White. “Reduction of model order based on proper orthogonal decomposition for lithium-ion battery simulations”. In: *Journal of the Electrochemical Society* 156.3 (2008), A154.
- [24] R Caldon, M Coppo, and R Turri. “Distributed voltage control strategy for LV networks with inverter-interfaced generators”. In: *Electric Power Systems Research* 107 (2014), pp. 85–92.

-
- [25] Lisa Calearo, Andreas Thingvad, and Mattia Marinelli. “Modeling of Battery Electric Vehicles for Degradation Studies”. In: *2019 54th International Universities Power Engineering Conference (UPEC)*. IEEE. 2019, pp. 1–6.
- [26] Jian Cao and Ali Emadi. “A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles”. In: *IEEE Transactions on power electronics* 27.1 (2011), pp. 122–132.
- [27] Rebecca Carter, Andrew Cruden, and Peter J Hall. “Optimizing for efficiency or battery life in a battery/supercapacitor electric vehicle”. In: *IEEE Transactions on Vehicular Technology* 61.4 (2012), pp. 1526–1533.
- [28] Pierpaolo Cazzola et al. “Global ev outlook 2016”. In: *International Energy Agency, France* (2016).
- [29] Nanophosphate High Power Lithium Ion Cell and ANR26650M1-B In MD100113. “Data Sheet; A123 Systems”. In: *Inc: Waltham, MA, USA* (2011).
- [30] Min Chen and Gabriel A Rincon-Mora. “Accurate electrical battery model capable of predicting runtime and IV performance”. In: *IEEE transactions on energy conversion* 21.2 (2006), pp. 504–511.
- [31] Yufei Chen and James W Evans. “Three-dimensional thermal modeling of lithium-polymer batteries under galvanostatic discharge and dynamic power profile”. In: *Journal of the Electrochemical Society* 141.11 (1994), p. 2947.
- [32] Aaron J Cheng et al. “Comparing the emissions benefits of centralized vs. decentralized electric vehicle smart charging approaches: A case study of the year 2030 California electric grid”. In: *Journal of Power Sources* 401 (2018), pp. 175–185.
- [33] Soo Seok Choi and Hong S Lim. “Factors that affect cycle-life and possible degradation mechanisms of a Li-ion cell based on LiCoO₂”. In: *Journal of Power Sources* 111.1 (2002), pp. 130–136.
- [34] J Christensen and J Newman. “Effect of anode film resistance on the charge/discharge capacity of a lithium-ion battery”. In: *Journal of the Electrochemical Society* 150.11 (2003), A1416.
- [35] Kyung Yoon Chung and Kwang-Bum Kim. “Investigations into capacity fading as a result of a Jahn–Teller distortion in 4 V LiMn₂O₄ thin film electrodes”. In: *Electrochimica Acta* 49.20 (2004), pp. 3327–3337.
- [36] Pablo Moreno-Torres Concha. “Analysis and Design Considerations of an Electric Vehicle Powertrain regarding Energy Efficiency and Magnetic Field Exposure”. PhD thesis. Universidad Politécnica de Madrid, 2016.

- [37] Domenico Di Domenico, Anna Stefanopoulou, and Giovanni Fiengo. “Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter”. In: *Journal of dynamic systems, measurement, and control* 132.6 (2010).
- [38] *Document Number: 3000489.1*. Tech. rep. Maxwell Technologies Ultracapacitors, 2014.
- [39] Marc Doyle, Thomas F Fuller, and John Newman. “Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell”. In: *Journal of the Electrochemical society* 140.6 (1993), p. 1526.
- [40] Marc Doyle et al. “Comparison of modeling predictions with experimental data from plastic lithium ion cells”. In: *Journal of the Electrochemical Society* 143.6 (1996), p. 1890.
- [41] Matthieu Dubarry et al. “Capacity loss in rechargeable lithium cells during cycle life testing: The importance of determining state-of-charge”. In: *Journal of Power Sources* 174.2 (2007), pp. 1121–1125.
- [42] Anamika Dubey and Surya Santoso. “Electric vehicle charging on residential distribution systems: Impacts and mitigations”. In: *IEEE Access* 3 (2015), pp. 1871–1893.
- [43] Madeleine Ecker et al. “Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data”. In: *Journal of Power Sources* 215 (2012), pp. 248–257.
- [44] Akram Eddahech et al. “Modeling and adaptive control for supercapacitor in automotive applications based on artificial neural networks”. In: *Electric power systems research* 106 (2014), pp. 134–141.
- [45] USEPA EPA. “Sources of greenhouse gas emissions”. In: *Retrieved December* (2017).
- [46] Mehrdad Eshani et al. “Modern electric, hybrid electric and fuel cell vehicles”. In: *Fundamentals, Theory, and Design*. Boca Raton, FL: CRC (2005).
- [47] Shaik Mullapathi Farooq et al. “Certificate Based Security Mechanisms in Vehicular Ad-Hoc Networks based on IEC 61850 and IEEE WAVE Standards”. In: *Electronics* 8.1 (2019), p. 96.
- [48] José María Fernández-Crehuet. *La conciliación de la vida profesional, familiar y personal*. 2016.
- [49] Christophe Forgez et al. “Thermal modeling of a cylindrical LiFePO₄/graphite lithium-ion battery”. In: *Journal of Power Sources* 195.9 (2010), pp. 2961–2968.

-
- [50] Abbas Fotouhi et al. “A review on electric vehicle battery modelling: From Lithium-ion toward Lithium–Sulphur”. In: *Renewable and Sustainable Energy Reviews* 56 (2016), pp. 1008–1021.
- [51] Rui Freire et al. “Integration of renewable energy generation with EV charging strategies to optimize grid load balancing”. In: *13th International IEEE Conference on Intelligent Transportation Systems*. IEEE. 2010, pp. 392–396.
- [52] Thomas F Fuller, Marc Doyle, and John Newman. “Relaxation phenomena in lithium-ion-insertion cells”. In: *Journal of the Electrochemical Society* 141.4 (1994), p. 982.
- [53] Thomas F Fuller, Marc Doyle, and John Newman. “Simulation and optimization of the dual lithium ion insertion cell”. In: *Journal of the Electrochemical Society* 141.1 (1994), p. 1.
- [54] Lijun Gao, Roger A Dougal, and Shengyi Liu. “Power enhancement of an actively controlled battery/ultracapacitor hybrid”. In: *IEEE transactions on power electronics* 20.1 (2005), pp. 236–243.
- [55] J García-Villalobos et al. “Multi-objective optimization control of plug-in electric vehicles in low voltage distribution networks”. In: *Applied Energy* 180 (2016), pp. 155–168.
- [56] Frederik Geth et al. “Voltage droop charging of electric vehicles in a residential distribution feeder”. In: *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*. IEEE. 2012, pp. 1–8.
- [57] Tanja Gewald et al. “Accelerated Aging Characterization of Lithium-ion Cells: Using Sensitivity Analysis to Identify the Stress Factors Relevant to Cyclic Aging”. In: *Batteries* 6.1 (2020), p. 6.
- [58] Evangelos G Giakoumis and Alexandros T Zachiotis. “Investigation of a diesel-engined vehicle’s performance and emissions during the WLTC driving cycle—comparison with the NEDC”. In: *Energies* 10.2 (2017), p. 240.
- [59] Petar J Grbovic. *Ultra-capacitors in Power Conversion Systems: Applications, Analysis, and Design from Theory to Practice*. John Wiley & Sons, 2013.
- [60] Sébastien Grolleau et al. “Calendar aging of commercial graphite/LiFePO₄ cell—Predicting capacity fade under time dependent storage conditions”. In: *Journal of Power Sources* 255 (2014), pp. 450–458.
- [61] Ting Guan et al. “Degradation mechanism of LiCoO₂/mesocarbon microbeads battery based on accelerated aging tests”. In: *Journal of Power Sources* 268 (2014), pp. 816–823.

- [62] Meng Guo, Godfrey Sikha, and Ralph E White. “Single-particle model for a lithium-ion cell: Thermal behavior”. In: *Journal of The Electrochemical Society* 158.2 (2010), A122.
- [63] Xuebing Han et al. “A comparative study of commercial lithium ion battery cycle life in electrical vehicle: Aging mechanism identification”. In: *Journal of Power Sources* 251 (2014), pp. 38–54.
- [64] Xuebing Han et al. “A review on the key issues of the lithium ion battery degradation among the whole life cycle”. In: *ETransportation* 1 (2019), p. 100005.
- [65] Fiona Harvey. “Four of world’s biggest cities to ban diesel cars from their centres”. In: *The Guardian* 2 (2016).
- [66] Yi-Jun He et al. “State of health estimation of lithium-ion batteries: A multiscale Gaussian process regression modeling approach”. In: *AIChE Journal* 61.5 (2015), pp. 1589–1600.
- [67] Patrick Hertzke, Nicolai Müller, and Stephanie Schenk. “Dynamics in the global electric vehicle-market”. In: *McKinsey, July* (2017).
- [68] Joris de Hoog et al. “Combined cycling and calendar capacity fade modeling of a Nickel-Manganese-Cobalt Oxide Cell with real-life profile validation”. In: *Applied Energy* 200 (2017), pp. 47–61.
- [69] Hai Huang et al. “Aging performances and cycle-life predictions of Li-ion battery”. In: *2016 35th Chinese Control Conference (CCC)*. IEEE. 2016, pp. 8710–8715.
- [70] Shaojun Huang et al. “Voltage support from electric vehicles in distribution grid”. In: *Power Electronics and Applications (EPE), 2013 15th European Conference on*. IEEE. 2013, pp. 1–8.
- [71] K Jalkanen et al. “Cycle aging of commercial NMC/graphite pouch cells at different temperatures”. In: *Applied Energy* 154 (2015), pp. 160–172.
- [72] Sung-Kyun Jung et al. “Understanding the degradation mechanisms of LiNi_{0.5}Co_{0.2}Mn_{0.3}O₂ cathode material in lithium ion batteries”. In: *Advanced Energy Materials* 4.1 (2014), p. 1300787.
- [73] Tariq Kamal et al. “Energy Management and Switching Control of PHEV Charging Stations in a Hybrid Smart Micro-Grid System”. In: *Electronics* 7.9 (2018), p. 156.
- [74] N Kaminski and R Schnell. “Thermal runaway during blocking”. In: *ABB Switzerland Ltd Semiconductors, Application Note 5SYA 2045-01* (2013).
- [75] Peter Keil and Andreas Jossen. “Aging of lithium-ion batteries in electric vehicles: Impact of regenerative braking”. In: *World Electric Vehicle Journal* 7.1 (2015), pp. 41–51.

-
- [76] Alireza Khaligh and Zhihao Li. “Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: State of the art”. In: *IEEE transactions on Vehicular Technology* 59.6 (2010), pp. 2806–2814.
 - [77] Hongrae Kim et al. “Inductor current measurement and regulation using a single DC link current sensor for interleaved DC–DC converters”. In: *IEEE transactions on power electronics* 26.5 (2010), pp. 1503–1510.
 - [78] Jung-Min Kim and Hoon-Taek Chung. “The first cycle characteristics of Li [Ni₁/3Co₁/3Mn₁/3O₂ charged up to 4.7 V”. In: *Electrochimica Acta* 49.6 (2004), pp. 937–944.
 - [79] Mithat C Kisacikoglu, Metin Kesler, and Leon M Tolbert. “Single-phase on-board bidirectional PEV charger for V2G reactive power operation”. In: *IEEE Transactions on Smart Grid* 6.2 (2015), pp. 767–775.
 - [80] Katarina Knezović and Mattia Marinelli. “Phase-wise enhanced voltage support from electric vehicles in a Danish low-voltage distribution grid”. In: *Electric Power Systems Research* 140 (2016), pp. 274–283.
 - [81] Tom P Kohler, Dominik Buecherl, and Hans-Georg Herzog. “Investigation of control strategies for hybrid energy storage systems in hybrid electric vehicles”. In: *2009 IEEE Vehicle Power and Propulsion Conference*. IEEE. 2009, pp. 1687–1693.
 - [82] Omar Laldin, Mazhar Moshirvaziri, and Olivier Trescases. “Predictive algorithm for optimizing power flow in hybrid ultracapacitor/battery storage systems for light electric vehicles”. In: *IEEE Transactions on power electronics* 28.8 (2012), pp. 3882–3895.
 - [83] Long Lam, Pavol Bauer, and Erik Kelder. “A practical circuit-based model for Li-ion battery cells in electric vehicle applications”. In: *2011 IEEE 33rd International Telecommunications Energy Conference (INTELEC)*. IEEE. 2011, pp. 1–9.
 - [84] Niels Leemput et al. “Impact of Electric Vehicle On-Board Single-Phase Charging Strategies on a Flemish Residential Grid.” In: *IEEE Trans. Smart Grid* 5.4 (2014), pp. 1815–1822.
 - [85] Niels Leemput et al. “Reactive power support in residential LV distribution grids through electric vehicle charging”. In: *Sustainable Energy, Grids and Networks* 3 (2015), pp. 24–35.
 - [86] Zhe Li et al. “A review of lithium deposition in lithium-ion and lithium metal secondary batteries”. In: *Journal of power sources* 254 (2014), pp. 168–182.
 - [87] Datong Liu et al. “Lithium-ion battery remaining useful life estimation based on nonlinear AR model combined with degradation feature”. In: *Annual conference of the prognostics and health management society*. Vol. 3. 2012, pp. 1803–1836.

- [88] Nima Lotfi et al. “Li-ion Battery State of Health Estimation based on an improved Single Particle model”. In: *2017 American Control Conference (ACC)*. IEEE. 2017, pp. 86–91.
- [89] Giacomo Lozzi, Valerio Gatta, and Edoardo Marcucci. “European urban freight transport policies and research funding: are priorities and H2020 calls aligned?”. In: *Region: the journal of ERSA* 5.1 (2018), pp. 53–71.
- [90] Languang Lu et al. “A review on the key issues for lithium-ion battery management in electric vehicles”. In: *Journal of power sources* 226 (2013), pp. 272–288.
- [91] W Lu et al. “Electrochemical performance of $\text{Li}_{4/3}\text{Ti}_5/3\text{O}_4/\text{Li}_{1+x}(\text{Ni}_{1/3}\text{Co}_{1/3}\text{Mn}_{1/3})_{1-x}\text{O}_2$ cell for high power applications”. In: *Journal of power sources* 167.1 (2007), pp. 212–216.
- [92] M Lucu et al. “A critical review on self-adaptive Li-ion battery ageing models”. In: *Journal of Power Sources* 401 (2018), pp. 85–101.
- [93] Srdjan M Lukic et al. “Energy storage systems for automotive applications”. In: *IEEE Transactions on industrial electronics* 55.6 (2008), pp. 2258–2267.
- [94] Srdjan M Lukic et al. “Power management of an ultracapacitor/battery hybrid energy storage system in an HEV”. In: *2006 IEEE Vehicle Power and Propulsion Conference*. IEEE. 2006, pp. 1–6.
- [95] Dingding Lv et al. “ $\text{Li}_2\text{O}-\text{B}_2\text{O}_3-\text{Li}_2\text{SO}_4$ modified $\text{LiNi}_{1/3}\text{Co}_{1/3}\text{Mn}_{1/3}\text{O}_2$ cathode material for enhanced electrochemical performance”. In: *Electrochimica Acta* 247 (2017), pp. 803–811.
- [96] Andrea Marongiu, Marco Roscher, and Dirk Uwe Sauer. “Influence of the vehicle-to-grid strategy on the aging behavior of lithium battery electric vehicles”. In: *Applied Energy* 137 (2015), pp. 899–912.
- [97] Francesco Marra et al. “Demand profile study of battery electric vehicle under different charging options”. In: *2012 IEEE Power and Energy Society General Meeting*. IEEE. 2012, pp. 1–7.
- [98] Sergejus Martinenas, Katarina Knezović, and Mattia Marinelli. “Management of power quality issues in low voltage networks using electric vehicles: Experimental validation”. In: *IEEE Transactions on Power Delivery* 32.2 (2017), pp. 971–979.
- [99] Hugo Mendonça et al. “Voltage Impact of a Wave Energy Converter on an Unbalanced Distribution Grid and Corrective Actions”. In: *Sustainability* 9.10 (2017), p. 1844.
- [100] Naoto Mizuta et al. “Synthesis of spatial charging/discharging patterns of in-vehicle batteries for provision of ancillary service and mitigation of voltage impact”. In: *IEEE Systems Journal* 13.3 (2018), pp. 3443–3453.

-
- [101] Hyung-Joo Noh et al. "Comparison of the structural and electrochemical properties of layered Li [NixCoyMnz] O₂ (x= 1/3, 0.5, 0.6, 0.7, 0.8 and 0.85) cathode material for lithium-ion batteries". In: *Journal of power sources* 233 (2013), pp. 121–130.
 - [102] Adnan Nuhic et al. "Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods". In: *Journal of power sources* 239 (2013), pp. 680–688.
 - [103] Noshin Omar et al. "Lithium iron phosphate based battery—Assessment of the aging parameters and development of cycle life model". In: *Applied Energy* 113 (2014), pp. 1575–1585.
 - [104] Hans Pacejka. *Tire and vehicle dynamics*. Elsevier, 2005.
 - [105] Stavros Papathanassiou, Nikos Hatziaargyriou, Kai Strunz, et al. "A benchmark low voltage microgrid network". In: *Proceedings of the CIGRE symposium: power systems with dispersed generation*. 2005, pp. 1–8.
 - [106] Meru A Patil et al. "A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation". In: *Applied energy* 159 (2015), pp. 285–297.
 - [107] Meru ADAGOUDA PATIL and Krishnan SEETHALAKSHMY HARIHARAN. *Method and apparatus for automatically estimating remaining useful life (RUL) of battery in real time*. US Patent 10,338,153. July 2019.
 - [108] Sebastian Paul et al. "Analysis of ageing inhomogeneities in lithium-ion battery systems". In: *Journal of Power Sources* 239 (2013), pp. 642–650.
 - [109] Roger D Perkins et al. "Controls oriented reduced order modeling of lithium deposition on overcharge". In: *Journal of Power Sources* 209 (2012), pp. 318–325.
 - [110] Martin Petit, Eric Prada, and Valérie Sauvant-Moynot. "Development of an empirical aging model for Li-ion batteries and application to assess the impact of Vehicle-to-Grid strategies on battery lifetime". In: *Applied energy* 172 (2016), pp. 398–407.
 - [111] Massimo Petricca et al. "Automated generation of battery aging models from datasheets". In: *2014 IEEE 32nd International Conference on Computer Design (ICCD)*. IEEE. 2014, pp. 483–488.
 - [112] Noah Daniel Pflugradt. "Modellierung von wasser und energieverbräuchen in haushalten". In: (2016).
 - [113] P Pillay, P Hofmann, and M Manyage. "Derating of induction motors operating with a combination of unbalanced voltages and over-or under-voltages". In: *IEEE Power Engineering Review* 22.7 (2002), pp. 51–51.
 - [114] P Pillay and M Manyage. "Definitions of voltage unbalance". In: *IEEE Power Engineering Review* 21.5 (2001), pp. 50–51.

- [115] Githin K Prasad and Christopher D Rahn. “Model based identification of aging parameters in lithium ion batteries”. In: *Journal of power sources* 232 (2013), pp. 79–85.
- [116] Lin Rao and John Newman. “Heat-generation rate and general energy balance for insertion battery systems”. In: *Journal of the Electrochemical Society* 144.8 (1997), p. 2697.
- [117] Venkat Rao et al. “Battery model for embedded systems”. In: *18th International Conference on VLSI Design held jointly with 4th International Conference on Embedded Systems Design*. IEEE. 2005, pp. 105–110.
- [118] Carl Edward Rasmussen. “Gaussian processes in machine learning”. In: *Summer School on Machine Learning*. Springer. 2003, pp. 63–71.
- [119] Roozbeh Razavi-Far, Shiladitya Chakrabarti, and Mehrdad Saif. “Multi-step-ahead prediction techniques for Lithium-ion batteries condition prognosis”. In: *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE. 2016, pp. 004675–004680.
- [120] Roozbeh Razavi-Far et al. “Data-driven prognostic techniques for estimation of the remaining useful life of lithium-ion batteries”. In: *2016 IEEE International Conference on Prognostics and Health Management (ICPHM)*. IEEE. 2016, pp. 1–8.
- [121] Yann G Rebours et al. “A survey of frequency and voltage control ancillary services—Part I: Technical features”. In: *IEEE Transactions on power systems* 22.1 (2007), pp. 350–357.
- [122] Eduardo Redondo-Iglesias, Pascal Venet, and Serge Pelissier. “Eyring acceleration model for predicting calendar ageing of lithium-ion batteries”. In: *Journal of Energy Storage* 13 (2017), pp. 176–183.
- [123] Eduardo Redondo-Iglesias, Pascal Venet, and Serge Pelissier. “Influence of the non-conservation of SoC value during calendar ageing tests on modelling the capacity loss of batteries”. In: *2015 Tenth International Conference on Ecological Vehicles and Renewable Energies (EVER)*. IEEE. 2015, pp. 1–5.
- [124] Guizhou Ren, Guoqing Ma, and Ning Cong. “Review of electrical energy storage system for vehicular applications”. In: *Renewable and Sustainable Energy Reviews* 41 (2015), pp. 225–236.
- [125] Grand View Research. *Lithium-ion Battery Market Size, Share and Trends Analysis Report By Product (LCO, LFP, NCA, LMO, LTO, Lithium Nickel Manganese Cobalt), By Application, By Region, And Segment Forecasts, 2020 - 2027*. Tech. rep. 2019.

-
- [126] Peter Richardson, Damian Flynn, and Andrew Keane. “Local versus centralized charging strategies for electric vehicles in low voltage distribution systems”. In: *IEEE Transactions on Smart Grid* 3.2 (2012), pp. 1020–1028.
- [127] Robert R Richardson, Michael A Osborne, and David A Howey. “Gaussian process regression for forecasting battery state of health”. In: *Journal of Power Sources* 357 (2017), pp. 209–219.
- [128] E Sarasketa-Zabala. “A Novel Approach for Li-ion Battery Selection and Lifetime Prediction”. PhD thesis. Tese (Doutorado)—Mondragon Goi Eskola Politeknikoa, 2014. 11, 13, 41, 44 . . ., 2014.
- [129] E Sarasketa-Zabala et al. “Calendar ageing analysis of a LiFePO₄/graphite cell with dynamic model validations: Towards realistic lifetime predictions”. In: *Journal of Power Sources* 272 (2014), pp. 45–57.
- [130] LH Saw et al. “Electro-thermal analysis of Lithium Iron Phosphate battery for electric vehicles”. In: *Journal of Power Sources* 249 (2014), pp. 231–238.
- [131] Johannes Schmalstieg et al. “A holistic aging model for Li (NiMnCo) O₂ based 18650 lithium-ion batteries”. In: *Journal of Power Sources* 257 (2014), pp. 325–334.
- [132] Julius Schmitt et al. “Impedance change and capacity fade of lithium nickel manganese cobalt oxide-based batteries during calendar aging”. In: *Journal of Power Sources* 353 (2017), pp. 183–194.
- [133] Bruno Scrosati and Jürgen Garche. “Lithium batteries: Status, prospects and future”. In: *Journal of power sources* 195.9 (2010), pp. 2419–2430.
- [134] Junyi Shen, Serkan Dusmez, and Alireza Khaligh. “Optimization of sizing and battery cycle life in battery/ultracapacitor hybrid energy storage systems for electric vehicle applications”. In: *IEEE Transactions on industrial informatics* 10.4 (2014), pp. 2112–2121.
- [135] Clarence M Shepherd. “Design of primary and secondary cells: II. An equation describing battery discharge”. In: *Journal of the Electrochemical Society* 112.7 (1965), p. 657.
- [136] Kandler A Smith, Christopher D Rahn, and Chao-Yang Wang. “Control oriented 1D electrochemical model of lithium ion battery”. In: *Energy Conversion and management* 48.9 (2007), pp. 2565–2578.
- [137] Kandler A Smith, Christopher D Rahn, and Chao-Yang Wang. “Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries”. In: *IEEE Transactions on Control Systems Technology* 18.3 (2009), pp. 654–663.

- [138] Alex J Smola and Bernhard Schölkopf. “A tutorial on support vector regression”. In: *Statistics and computing* 14.3 (2004), pp. 199–222.
- [139] Robert Spotnitz. “Simulation of capacity fade in lithium-ion batteries”. In: *Journal of power sources* 113.1 (2003), pp. 72–80.
- [140] EN50160 Standard et al. “Voltage characteristics of electricity supplied by public distribution systems”. In: *BS EN 50160* (2010).
- [141] Daniel-Ioan Stroe et al. “Degradation behavior of lithium-ion batteries during calendar ageing—The case of the internal resistance increase”. In: *IEEE Transactions on Industry Applications* 54.1 (2017), pp. 517–525.
- [142] Shun Sun et al. “Changes of degradation mechanisms of LiFePO₄/graphite batteries cycled at different ambient temperatures”. In: *Electrochimica Acta* 237 (2017), pp. 248–258.
- [143] Uwe Tietge et al. “Comparison of leading electric vehicle policy and deployment in Europe”. In: *International Council on Clean Transportation* 49 (2016).
- [144] Olivier Tremblay and Louis-A Dessaint. “Experimental validation of a battery dynamic model for EV applications”. In: *World electric vehicle journal* 3.2 (2009), pp. 289–298.
- [145] Olivier Tremblay, Louis-A Dessaint, and Abdel-illah Dekkiche. “A generic battery model for the dynamic simulation of hybrid electric vehicles”. In: *2007 IEEE Vehicle Power and Propulsion Conference*. Ieee. 2007, pp. 284–289.
- [146] Maria Varini, Pietro Elia Campana, and Göran Lindbergh. “A semi-empirical, electrochemistry-based model for Li-ion battery performance prediction over life-time”. In: *Journal of Energy Storage* 25 (2019), p. 100819.
- [147] Marina Gonzalez Vaya and Göran Andersson. “Centralized and decentralized approaches to smart charging of plug-in vehicles”. In: *Power and Energy Society General Meeting, 2012 IEEE*. IEEE. 2012, pp. 1–8.
- [148] Pallavi Verma, Pascal Maire, and Petr Novák. “A review of the features and analyses of the solid electrolyte interphase in Li-ion batteries”. In: *Electrochimica Acta* 55.22 (2010), pp. 6332–6341.
- [149] Jens Vetter et al. “Ageing mechanisms in lithium-ion batteries”. In: *Journal of power sources* 147.1-2 (2005), pp. 269–281.
- [150] Aiping Wang et al. “Review on modeling of the anode solid electrolyte interphase (SEI) for lithium-ion batteries”. In: *npj Computational Materials* 4.1 (2018), pp. 1–26.

-
- [151] Hainan Wang and Laurent Pilon. “Mesoscale modeling of electric double layer capacitors with three-dimensional ordered structures”. In: *Journal of Power Sources* 221 (2013), pp. 252–260.
- [152] John Wang et al. “Cycle-life model for graphite-LiFePO₄ cells”. In: *Journal of power sources* 196.8 (2011), pp. 3942–3948.
- [153] John Wang et al. “Degradation of lithium ion batteries employing graphite negatives and nickel–cobalt–manganese oxide+ spinel manganese oxide positives: Part 1, aging mechanisms and life estimation”. In: *Journal of Power Sources* 269 (2014), pp. 937–948.
- [154] Yaw-Juen Wang and Lambert Pierrat. “A method integrating deterministic and stochastic approaches for the simulation of voltage unbalance in electric power distribution systems”. In: *IEEE Transactions on Power Systems* 16.2 (2001), pp. 241–246.
- [155] Sam Weckx and Johan Driesen. “Load balancing with EV chargers and PV inverters in unbalanced distribution grids”. In: *IEEE Transactions on Sustainable Energy* 6.2 (2015), pp. 635–643.
- [156] Randy Ben Wright et al. “Calendar-and cycle-life studies of advanced technology development program generation 1 lithium-ion batteries”. In: *Journal of power sources* 110.2 (2002), pp. 445–470.
- [157] CH Wu, YH Hung, and CW Hong. “On-line supercapacitor dynamic models for energy conversion and management”. In: *Energy Conversion and Management* 53.1 (2012), pp. 337–345.
- [158] Rui Xiong et al. “An electrochemical model based degradation state identification method of Lithium-ion battery for all-climate electric vehicles application”. In: *Applied Energy* 219 (2018), pp. 264–275.
- [159] Yonghuang Ye et al. “Electro-thermal modeling and experimental validation for lithium ion battery”. In: *Journal of Power Sources* 199 (2012), pp. 227–238.
- [160] Ali Zenati, Ph Desprez, and Hubert Razik. “Estimation of the SOC and the SOH of li-ion batteries, by combining impedance measurements with the fuzzy logic inference”. In: *IECON 2010-36th Annual Conference on IEEE Industrial Electronics Society*. IEEE. 2010, pp. 1773–1778.
- [161] Chaolong Zhang et al. “Capacity prognostics of lithium-ion batteries using EMD denoising and multiple kernel RVM”. In: *IEEE Access* 5 (2017), pp. 12061–12070.
- [162] Lei Zhang et al. “A comparative study of equivalent circuit models of ultracapacitors for electric vehicles”. In: *Journal of Power Sources* 274 (2015), pp. 899–906.

- [163] Lei Zhang et al. “A review of supercapacitor modeling, estimation, and applications: A control/management perspective”. In: *Renewable and Sustainable Energy Reviews* 81 (2018), pp. 1868–1878.
- [164] Wei-Jun Zhang. “Structure and performance of LiFePO₄ cathode materials: A review”. In: *Journal of Power Sources* 196.6 (2011), pp. 2962–2970.
- [165] Zhiyun Zhang et al. “Prediction of Lithium-ion battery’s remaining useful life based on relevance vector machine”. In: *SAE International Journal of Alternative Powertrains* 5.1 (2016), pp. 30–40.
- [166] Fang Zhou et al. “Adaptive model predictive control-based energy management for semi-active hybrid energy storage systems on electric vehicles”. In: *Energies* 10.7 (2017), p. 1063.
- [167] Xin Zhou, Jeffrey L Stein, and Tulga Ersal. “Battery state of health monitoring by estimation of the number of cyclable Li-ions”. In: *Control Engineering Practice* 66 (2017), pp. 51–63.
- [168] Yapeng Zhou and Miaohua Huang. “Lithium-ion batteries remaining useful life prediction based on a mixture of empirical mode decomposition and ARIMA model”. In: *Microelectronics Reliability* 65 (2016), pp. 265–273.
- [169] Yapeng Zhou et al. “A novel health indicator for on-line lithium-ion batteries remaining useful life prediction”. In: *Journal of Power Sources* 321 (2016), pp. 1–10.
- [170] Cong Zhu et al. “Development of a theoretically based thermal model for lithium ion battery pack”. In: *Journal of Power Sources* 223 (2013), pp. 155–164.
- [171] Changfu Zou et al. “Multi-time-scale observer design for state-of-charge and state-of-health of a lithium-ion battery”. In: *Journal of Power Sources* 335 (2016), pp. 121–130.