“Investigating Hybrid Battery configuration for Solar Home Systems”

Papakosta Thekla

Master of Science Thesis

TU Delft

Cover page source:*[trevolution.com.au]*

Investigating Hybrid Battery configuration for Solar Home Systems

By

Papakosta Thekla
Παπακώστα Θέκλα

in partial fulfilment of the requirements for the degree of

Master of Science
in Faculty of Electrical Engineering, Mathematics and Computer Science

at the Delft University of Technology,
to be defended publicly on Tuesday October 24, 2017 at 13:30 AM.

Supervisor:	Prof.dr.ir. P. Bauer	
Thesis committee:	Prof.dr.ir. P. Bauer,	DCE&S group TU Delft
	Dr.ir.Zian Qin,	DCE&S group TU Delft
	Prof.dr .A.H.M. Smets,	PVMD group TU Delft

TU Delft

Acknowledgments

"Life begins at the end of your comfort zone"
Neale Donald Walsch

To my parents, who have pushed me and given me the confidence to take risks being my life coaches.

My special gratitude and appreciation goes to my thesis supervisors, Dr.ir.Jelena Popovic for giving me the opportunity to work for this project and Professor Dr. ir. Pavol Bauer for guiding me and giving me valuable feedback.

My special appreciation goes to my daily supervisor Nishant for pushing me when he had to, for lifting my spirit in times that I lost confidence, for setting high standards and mostly for his valuable guidance and advices that always come with some humour. I would also like to thank Victor for giving me valuable advice and for working together during a paper. Thank you for all the free coffee too!

All of my office-mates deserve a special mention as they made my days in the office much more fun. I would like to thank Yun He for giving me her valuable insights about batteries, Natalie, Michalis and Wenrui for having small talks as well meaningful long conversations in times when no one wanted to work.

From the bottom of my heart I want to thank my friends from SET, Nikos, Ilias and Kostas for going through this master with me, my Architect friends, Antigoni, Kalia, Maria for showing real interest in my project even though they had no idea what I was talking about most of the times. I especially want to thank all of my roommates, Alex, Giannis, Angelos, Dimitris for standing by me even when I was cranky and in a bad mood.

I want to give special thanks to Panos, Antria, Maria, Ioana, Themos and Constantinos because each one of them went out of their way to support me.

All of my Cypriot friends deserve a special mention as they have been constantly next to me in every step of my studies, even though they were far away.

And finally last but by all means not least, my sisters for always being there for me unconditionally,Eirene, Margarita, Styliani. My very special appreciation goes to Eirene for supporting me and providing me with a warm plate of great food as well as making my house a warm and welcoming place in the last months of my thesis.

Papakosta Thekla
Delft, October 2017

Abstract

The fact that the developing world struggles to cover even the most basics of needs, in contrast to the developed world, is tangibly connected to the lack of electricity. As many developing nations, especially the ones located in rural areas, face many difficulties to access the grid, alternative stand-alone solutions such as Solar Home Systems (SHS) have been proposed and used already for a while. The main technical limitation plaguing SHSs is the necessity of including a storage device that mitigates the energy difference between production and demand. Batteries are the components that experience the shortest lifetime and highest cost in stand-alone PV systems such as SHSs.

This study aims to explore and find the most suitable and viable storage option in terms of lifetime and costs for certain load cases concerning SHS applications. In order for this to be achieved, single battery options, as well as Hybrid battery options, were examined.

For the comparison of the different battery technologies with the different Hybrid battery configurations, lifetime and costs had to be taken into account. For this purpose a non-empirical dynamic battery lifetime estimation method was modelled and applied to four different battery technologies and a variety of different Hybrid battery combinations. The battery technologies examined in this thesis are Lithium iron phosphate (LiFePO4), Sealed lead-acid (VRLA), Nickel-Cadmium (NiCd) and Flooded lead-acid. This method takes into account different DOD (Depth of Discharge) levels, Temperature effects and lifetime curves extracted from different datasheets for the different technologies, in order to be able to model the different battery behaviours as accurately as possible.

For the modelling of the different Hybrid battery configurations two different power management schemes were constructed and applied to the dynamic lifetime estimation that is proposed. This method was validated and concluded to be realistic as it was able to capture the different battery characteristics for the different technologies.

For the comparison of the different storage options, a singular function was constructed for both single and hybrid battery options. This function quantifies both upfront and lifetime battery costs while, at the same time, captures the future battery cost trends that are foreseen for different technologies. This function was used as the point of reference in the comparison of every storage option that was tested.

The optimum storage option that minimizes the battery cost function for the two sets of PV-load Case studies used in this project, was found to be a Hybrid battery that consists of LiFePO4 and Sealed lead-acid technology, with different sizes and configurations.

In conclusion, the lifetime method proposed as well as the battery cost function constructed could be easily adopted and used for a variety of different battery technologies in low-power applications. A prerequisite for the above mentioned realization is that cycle life data of the examined technology are either provided or easy to be constructed.

Papakosta Thekla
Delft, October 2017

Table of Contents

List of Figures

List of Tables

List of abbreviations and Symbols

- ***List of Abbreviations***

b.c.f	Battery Cost Function
DOD	Depth Of Discharge
EOL	End Of Life
HB	Hybrid Battery
h.b.c.f	Hybrid Battery Cost Function
LiFePO4	Lithium Iron Phosphate
LP	Load Profile
LLP	Loss of Load Probability
PM A	Power Management A
PM B	Power Management B
PV	Photovoltaic
R&D	Research And Development
SEI	Solid Electrolyte Interface
SHS	Solar Home System
SOC	State Of Charge
SOH	State Of Health
VRLA	Valve Regulated Lead Acid
Wh	Watt hour

- ***List of Symbols***

η_{batt}	Roundtrip efficiency
η_v	Voltaic efficiency
η_c	Coulombic efficiency
E	Number of events
E_{out}	Output energy of the battery
E_{in}	Input energy of the battery
E_{nom}	Nominal battery capacity
$E_{thr,tot}$	Total energy throughput
$V_{charhing}$	Average charging voltage
$V_{discharging}$	Average discharging voltage
$Q_{discharge}$	Output charge
Q_{charge}	Input charge
Q_t	Real time battery capacity
Q_N	Nominal battery capacity
T_{ref}	Reference temperature
T_{avg}	Average temperature
S	Battery size
SOC_{dev}	SOC standard deviation
SOC_{avg}	Average SOC
DOD_{avg}	Average DOD
D	Damage
R	Number of replacements
N	Number of cycles until EOL

C	Battery Cost factor
L	Battery lifetime in years
t_0	System installation year
t_{repl}	Year of replacements
r	Battery capacity percentage
n	Number of cycles
d	Battery DOD
f	Linear factor
cl	Cycle life of battery
cf	Capacity fading
σ	Capacity fading tress factor
ξ	Capacity fated (Ah)

Chapter 1

Introduction

1.1. Motivation of Thesis

The fact that developing nations and communities around the world suffer from poverty, unemployment, lack of education and very low levels of life quality is tangibly connected with the lack of electricity. All these problems were addressed in the modern world with the use of electricity enabling so many conveniences and technological advancements, increasing the quality of life drastically.

The depletion of fossil fuels combined with the green-house gas emission problem that leads to climate change made the use of renewable energy technologies a need. Batteries represent one of the most important components in systems like these as well as one of their biggest limitation, driving many scientists and researchers to be dealing extensively with projects that aim to minimize battery cost and maximize its lifetime, finding the most effective and optimal storage for different renewable applications.

Many developing regions in Sub-Saharan Africa and South Asia do not have robust grid connection, and are far away from having one, due to many technical issues that come with the grid extension procedure. Solar Home Systems (SHS) are one effective solution to this grid extension problem as they are defined as low power, low cost, off grid PV systems. The energy time mismatch between PV generation and load demand, in such systems, needs to be mitigated with a storage unit. Even though batteries are an essential component of the SHSs, are also considered to be their main problem mainly due to their high cost and low lifetime. While cost is a very important factor in applications taking place in developing countries, lifetime is also important because it increases the overall cost of the system.

The need for a more cost effective energy storage, the authors growing interest in clean and renewable technologies combined with her passion in helping increasing the socio-economic quality of life that can also bring amongst all the other advances women empowerment in developing nations, have led to this project.

1.2. Objectives and Research Questions

The main objective of this thesis is to examine whether and which Hybrid Battery configuration will be the optimal choice in terms of combined lifetime and costs to be used in a Solar Home System application in a specific chosen location, taking into account specific sets of PV-production and load profiles. In order for this to be achieved, many sub-questions need to be answered first.

Main Research Question

Which optimal Battery Technology or Hybrid Battery configuration can optimize the storage cost function for a given set of PV-Load profile?

Sub-Research Questions

- What is the Optimal Storage Size for different Load Scenarios taking place in a specified location?
- How to accurately estimate the lifetime of a battery taking into account as many battery parameters and behaviours as possible for different battery technologies?

- How can the upfront and lifetime costs be combined into a singular cost function while capturing the future cost trends of the different technologies?

- Which are the limitations of individual battery technologies? How the hybrid battery will combine the best features of each technology?

1.3. Unique contributions of the Thesis

Apart from reaching its main goal this thesis project has some other intermediate contributions that helped reach the initial objective and can be adopted and used in many other cases and applications apart from Solar Home Systems. These individual contributions are:

- The implementation of a non-empirical Dynamic lifetime battery model, that was conducted taking into account various battery parameters and behaviours as well as compared and validated with empirical models.

- The formulation of a combined cost function which enables different storage option comparisons, that takes into account upfront and lifetime battery costs, including sizing and replacements and captures the future trends of the battery costs for different technologies.

1.4. Thesis Outline

The thesis report is divided in 7 chapters. Figure 1-1 illustrates how this report is organized.

Chapter 1 – Introduction This chapter consists of a short introduction underlying the motivation and defining the research questions of this thesis as well as the unique contributions of this work.

Chapter 2 – Solar Home Systems This chapter aims to provide a background for Solar Home Systems focusing mostly on the battery and its usage in systems like that. An overview of the battery parameters and a comparison of different battery technologies are also given. In addition, the physical aging mechanisms of the different battery technologies and an overview of already existing capacity fading and lifetime estimation studies are explained.

Chapter 3 – Storage sizing in SHSs – Case Studies The first section of this chapter consists of the case studies, sets of PV-load profiles that were used. The second section discusses a methodology for sizing the storage in a Solar Home Systems for the two different load cases that were taken into account. A detailed description of the procedure that was followed and the results for the different scenarios are also presented and discussed.

Chapter 4 – Battery Lifetime Estimation This chapter includes of a classification of different lifetime estimation models explaining them in detail and how they fit or not into the model that is constructed in this thesis. Furthermore, the methodology that was followed step by step, for the non-empirical dynamic battery lifetime estimation model and how it is validated as well as the results retrieved, are presented and explained.

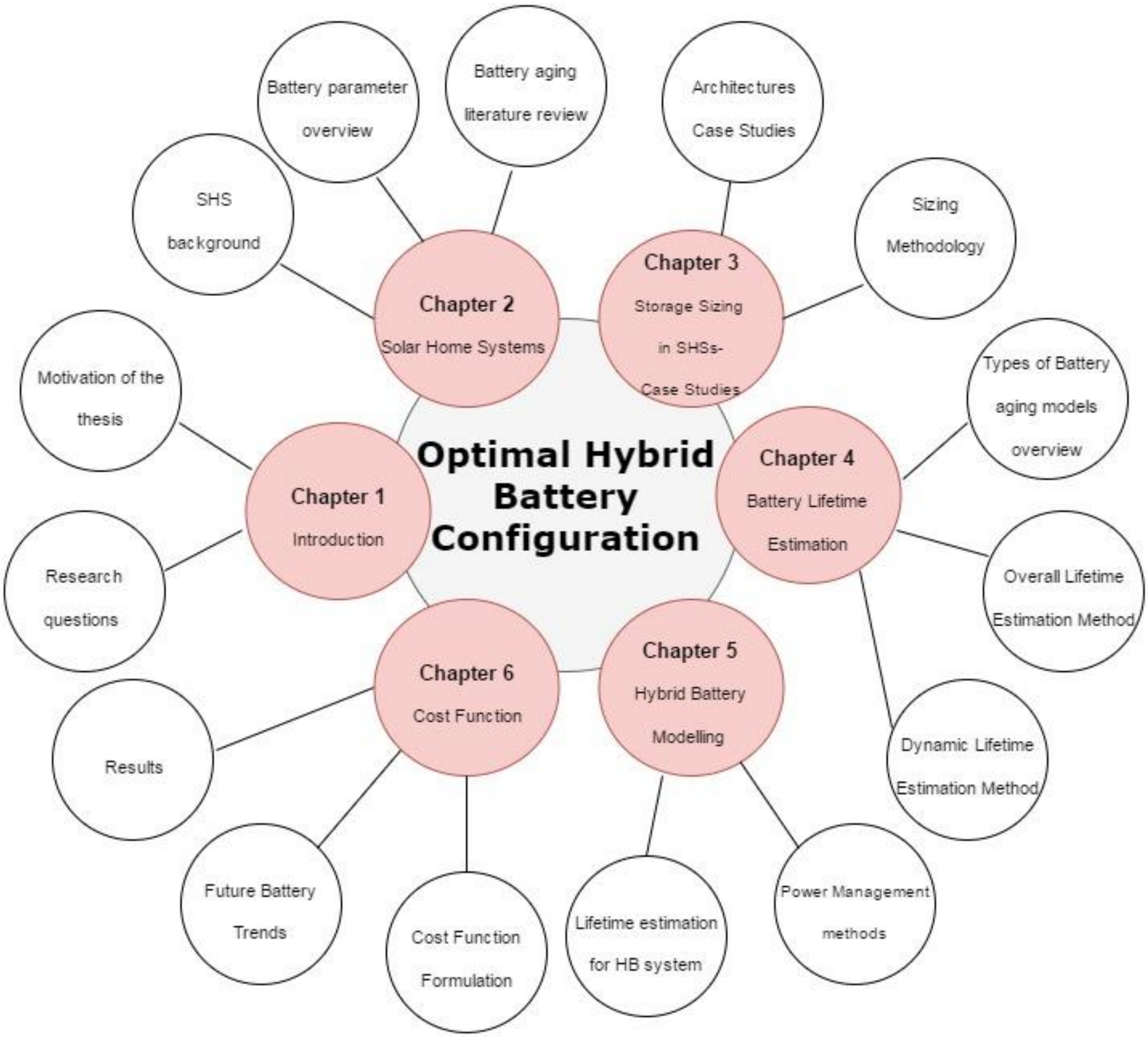


Figure 1-1: Outline of the thesis

Chapter 5 – Hybrid Battery modelling This chapter has as main goal to present the two power management methods that were conducted for the Hybrid Battery System. In addition, the way that the power management methods can be combined with the lifetime estimation method proposed in chapter 4, is explained analytically.

Chapter 6 – Cost Function This chapter aims to explain the theoretical background behind the decision of conducting the cost function. The formulation of the battery and hybrid battery cost functions are shown with their units and the parameters that are taken into account for this cost function. A sensitivity analysis regarding the future battery costs is carried out. The results of the cost function for all the battery technologies used and all the hybrid battery combinations, are presented and discussed at the end of this chapter.

Chapter 7 – Conclusions and Recommendations This chapter summarizes the results of this project answering the research questions and discusses further improvements recommending some solutions for further studies.

Chapter 2

Solar Home Systems

This chapter introduces the technology of Solar Home Systems and their main technical limitations. The importance of batteries in Solar Home Systems is underlined and the battery technologies with their different characteristics that are used for this study are introduced. In addition, different battery aging physical mechanisms and different battery parameters that affect battery aging are explained. Lastly, a battery modelling classification takes place as well as different existing battery models.

2.1. Introduction

2.1.1. Current Status of rural electrification

It has been evident that nowadays, nearly 1.2 billion people do not have access to electricity. This number is translated to 17% of the global population. It is also a fact that 80% of those lacking electricity live in rural areas with Sub-Saharan Africa and South Asia to be possessing 95% of this percentage [1]. Figure 2-1 shows how the energy poverty which is defined as the lack of access to electricity is distributed throughout the world.

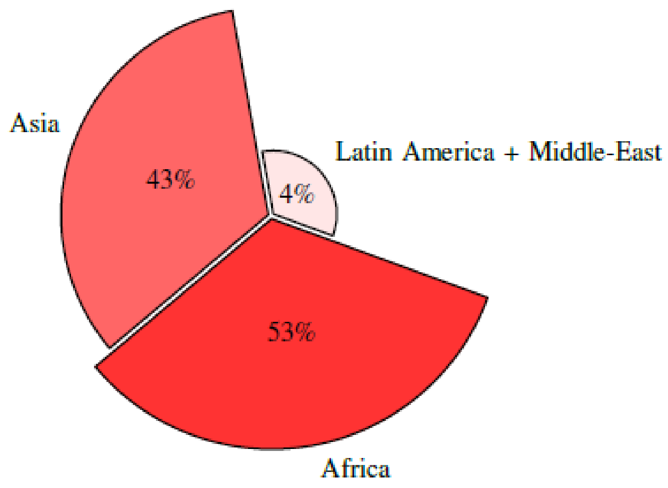


Figure 2-1: How the lack of electricity is distributed worldwide [as shown [2]]

It is impossible for a nation to reduce its poverty levels without the use of energy, something that imposes access to electricity. Therefore, in order for the developing areas to progress, the use of electricity is substantial [3].

In an effort to reduce this lack of electricity in developing countries, many off grid energy production concepts have been invented as well as implemented. High transmission and distribution costs combined with practical difficulties that occur such as the need of very long cables, make the extension of the national grid a less viable and immediate solution increasing the popularity of the off grid solutions [4]. Solar Home Systems appear to be a very promising idea in addressing these electricity problems. The fact that these areas mostly lie in latitudes with high sun irradiation makes them suitable for the use of off grid PV systems.

2.1.2. **Solar Home Systems (SHS) in Developing Nations**

"As the developed world addresses the challenges of meeting sustainability targets, the developing world simply struggles to provide universal electricity coverage" [5]. Within that framework, clean energy technology markets such as Solar Home Systems have progressed and grown significantly over the past years, giving access to electricity to millions of people worldwide. The largest amount of global off-grid population is concentrated in the remote rural areas of developing countries, thus Solar Home System development targets people living in these areas, otherwise called as Base of Pyramid (BoP) [6].

A Solar Home System is a low cost low energy off grid PV System that is rated between 50 W to 250 W and includes a battery storage unit. These systems are able to power small lights and cell phone chargers or in some cases a television and a small fan. They are mostly designed to serve the basic energy needs of a single household and sometimes they are expanding to a neighbourhood or a community level.

2.1.3. **Main Challenges of Solar Home Systems**

One of the main disadvantages of Renewable Energy Technologies is the energy mismatch occurs between the energy production and energy demand. Storage technologies are able to effectively reduce this mismatch by storing energy in times with excess of energy production and using it in times with energy deficit [7]. Thus, storage units are one of the most important elements in a Renewable Energy System. Off-grid PV Systems such as Solar Home Systems are not an exception as they too require a storage unit.

Having this in mind, one of the main and the most important limitations of Solar Home Systems, is considered to be their high upfront and lifetime cost. The upfront costs for all the different components consisting an SHS are shown in Figure 2-2.

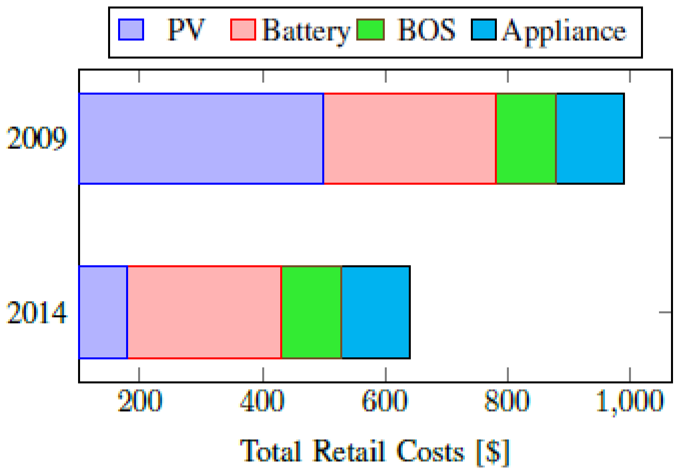


Figure 2-2: Initial costs of components of SHS in 2009 and 2014 [as shown [2]]

It is evident that while the PV costs have fallen significantly for the past years the battery costs have remained almost the same. In addition, the upfront cost of the battery combined with its low lifetime makes it the most expensive component in such systems. While the lifetime of the PVs can reach up to 25 years, the battery lifetime for these applications can vary between 3-10 years, meaning that the battery is going to need occasional replacement, increasing further the total cost of the system [8].

2.2. *Battery Storage-Different Technologies-characteristics-Use in Solar Home Systems*

2.2.1. **Battery Technologies - General Information**

There are three main types of battery technologies that are going to be discussed in detail and used in this project. These technologies are Lead-acid batteries, Lithium-based batteries and Nickel based batteries.

Lead-Acid Batteries: Lead-acid batteries are divided into two main categories, flooded or vented and sealed or valve regulated batteries (SLA or VRLA). The main differences between these two types of batteries are that the VRLAs do not need upright orientation, ventilated environment or routine maintenance in order to perform properly while flooded lead-acid batteries require all of the above [9]. A schematic representation of a lead acid cell is shown in Figure 2-3.

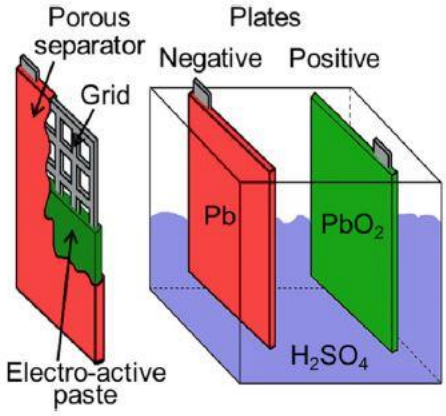


Figure 2-3: Schematic Representation of lead-acid batteries [as shown in [10]]

Lithium-Based Batteries: Lithium based batteries can be generally divided into two categories also, Lithium-ion Phosphate (LFP, $LiFePO_4$) and metal oxides (NCM, NCA, Cobalt, Manganese) [9]. Li-Phosphate batteries exhibit higher tolerance to full charge conditions and less stress than other lithium ion systems while at the same time operate in lower nominal voltage [11] . Lithium metal cells, on the other hand, have the ability to retain higher power outputs [12] . A simple representation of lithium ion battery cells is shown in Figure 2-4.

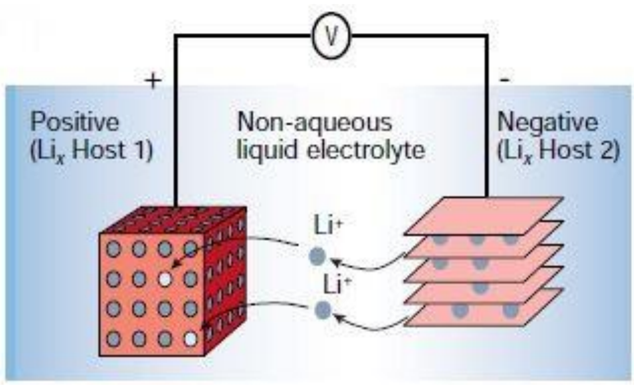


Figure 2-4: Schematic representation of lithium ion cells [as shown in [13]]

Nickel-Based Batteries: Nickel-based batteries are divided into Nickel-Cadmium (NiCd) and Nickel Metal Hydrides (NiMH). For the first technology the anode material contains Cadmium, which was replaced in the latter technology by metal hydride because of its toxicity [12] . An illustration of NiCd cells is shown in Figure 2-5.

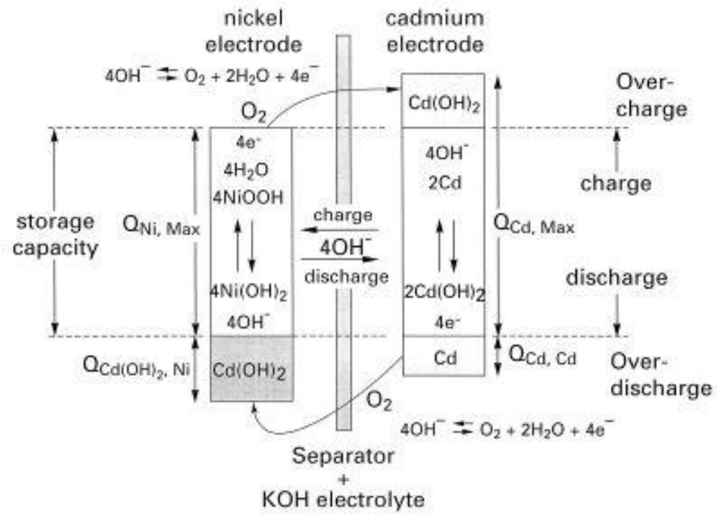


Figure 2-5: Schematic representation of NiCd cell [as shown in [14]]

2.2.2. Battery Characteristics

Lead-Acid Batteries

Lead Acid batteries are one of the most used battery technologies, nowadays. One of their main characteristics as well as main advantage is that they are dependable and inexpensive on cost/Watt and simple to manufacture. Moreover lead-acid batteries are characterized by experiencing the lowest-self discharge among the rechargeable battery technologies and high specific power.

However, they are heavier and less durable than other battery technologies such as lithium and nickel-based systems, especially when deep cycled. In general, these batteries exhibit short cycle life due to various reasons which are going to be discussed later in this chapter.

While lead-acid batteries have moderate life span they don't present memory effects as Nickel-based batteries do. In addition, their performance is high at cold temperatures making them a more suitable technology at subzero conditions than lithium based batteries.

Similar to all battery types, their capacity fades gradually while cycling. Furthermore, these types of batteries are able to deliver high current having a small response time. In terms of environmental considerations the lead and sulphuric materials are harmful and unfriendly to the environment. Some of the main limitations of lead-acid batteries are, their low specific energy, slow charge rates and the fact that when stored they have to be at charged conditions in order to prevent sulfation [15].

Lithium-Based Batteries

Lithium Ion batteries are one of the most popular battery types especially for residential as well as portable electronics. They are the most lightweight batteries amongst all the battery technologies having very high energy density as lithium is a highly reactive element. For example, 1 kilogram of lithium ion batteries can store the same amount of energy that can be stored in 6 kilograms of lead-acid batteries.

The capacity fading in lithium ion batteries is very small especially compared to Nickel based batteries, losing 5 % of their initial capacity per month of use instead of the 20 % loss that Nickel-based experience. In addition, lithium ion batteries have no memory effect which is significant in Nickel-based batteries. The most important advantage of lithium ion batteries is their long cycle life making them able to handle thousands of charge-discharge cycles throughout their lifetime.

On the other hand, lithium ion batteries exhibit very high calendar life effects losing a significant amount of their initial capacity when stored. The cell degradation is more severe when the cell is exposed in extreme and especially high temperatures. One of the most important disadvantages of lithium-ion batteries is their high cost, making them highly competitive technology with lead acid [16].

Nickel-Based Batteries

Nickel based batteries or otherwise alkaline batteries have many common characteristics between the different chemistries but they also differentiate in some aspects. Some of the common advantages that these technologies have are their low internal resistance and high energy density as well as their deep cycle ability. One of their most important advantage is that they are able to operate in a wide range of temperatures, greater than lead-acid, without losing their efficiency or be damaged. In addition, alkaline batteries are able to support a certain amount of overcharge without experiencing electronic failure.

On the other hand, their increased memory effect coupled with the fact that they deteriorate after a long time of storage are their main limitations. In addition to that, their energy density is considered to be 60% or less than lithium ion batteries depending on the battery chemistry.

The most common alkaline technologies are NiCd and NiMH batteries. Their differences mostly lie in their energy density, with NiMH having 50% higher energy density than Nicads. Lastly, NiMH are environmentally friendly in contrast with NiCd that contain cadmium which a highly harmful material [17] [18] [19].

A comparison between the different battery technologies and the main battery parameters that are examined in this project is shown in Table 1**.**

Table 1: Comparison of different battery characteristics [20] [21].

Battery Technology	Energy Efficiency [%]	Cycle Life [-]	Temperature Performance	Cost [$/kWh]
Sealed Lead-acid	70-95	Moderate	Low when cold	100-200
Flooded Lead-acid	72-78	Moderate	Low when cold	100-200
Lithium ion	90-95	High	Low when cold	300-600
Nickel Cadmium (NiCd)	72-78	High	-50 to 70 C	300-1000

2.2.3. Battery Parameters - An overview

In this section many battery parameters that will be used later in the modelling are going to be introduced and a brief overview of these parameters will be presented.

Battery Cycling

Battery cycling is the process at which the battery charges and discharges undergoing different levels of charge or discharge. In general, battery cycling expresses the total battery usage.

Cycle Life

Cycle life is defined as the number of cycles, full charging/discharging that the battery undergoes until it reaches the End-of-life. For most manufacturers the End-of-life is the point at which the battery loses 20% of its initial capacity.

Battery Efficiency

The battery efficiency or otherwise roundtrip efficiency is defined as the ratio of the output energy of the battery to the input energy of the battery as shown in Equation 2.1.

$$\eta_{bat} = \frac{E_{out}}{E_{in}} \tag{2.1}$$

This roundtrip efficiency can be divided into two categories, voltaic efficiency and coulombic efficiency. Voltaic efficiency is the average discharging voltage of the battery divided by the average charging voltage of the battery while coulombic efficiency is the ratio between the total charge that was extracted from the battery with the total charge that was fed into the battery over the time of a full cycle. Voltaic and coulombic efficiencies can be expressed by the Equations 2.2 and 2.3, respectively [22].

$$\eta_V = \frac{V_{discharge}}{V_{charge}} \tag{2.2}$$

$$\eta_C = \frac{Q_{discharge}}{Q_{charge}} \tag{2.3}$$

Capacity Fading

As the battery cycles or being stored, its capacity is reduced irreversibly having as a result for the maximum available charge to be less than the nominal value. This procedure is called capacity fading.

State of Charge (SOC)

Sate of charge is a measure that indicates the percentage of the charge that is left in the battery after charging it or discharging it. 100% SOC corresponds to fully charged battery and 0% SOC corresponds to a fully discharged battery. Most manufacturers state that it is better to keep the SOC of the battery between the range between 20% to 80 % in order to maintain better lifetime for the battery. The state of charge of the battery can be defined as the ratio between the current battery capacity divided by the overall-maximum or otherwise nominal battery capacity (Q_N) as shown in Equation 2.4 [23].

$$SOC = \frac{Q_t}{Q_N} \tag{2.4}$$

Depth of Discharge (DOD)

The percentage of the charge that is withdrawn from the battery after being charged or discharged is called Depth of Discharge. In other words DOD is a measurement of how deeply the battery has been discharged. 100 % DOD indicates that the battery is empty and 0 % of DOD indicates that the battery is fully charged. The Depth of Discharge is expressed by Equation 2.5 [24] [25].

$$DOD = 1 - SOC = 1 - \frac{Q_t}{Q_N} \tag{2.5}$$

C-rate

C-rate is a measure of how fast the battery is able to fully charge and discharge. For example 1C means that the battery is fully discharged in an hour, while 0.5 C means that the battery is fully discharged in 2 hours, etc.

State of Health (SOH)

State of Health is an indicator of the battery's conditions at a certain time compared to its ideal conditions. More specifically, it is a measure over time that reflects the current state of the battery and how much of its capacity has been consumed through time. SOH is represented as a percentage with 100% meaning that the battery is fresh. It can be derived by many battery parameters, such as impedance, self-discharge rate, power density but the most common one is the battery capacity. More specifically, it could be considered as the ratio of the current battery capacity with the initial, rated capacity given in the specifications. When the SOH reaches 80%, meaning that the battery capacity is 20% less than the initial value, then the battery should be replaced [26].

End-of-life (EOL)

End-of-life is a measurement that indicates the point at which the battery needs replacement after undergoing aging and fading. Most manufacturers and researchers state that the End-of-life of the battery is when it reaches 80% of its initial capacity [27]. After this percentage the battery is still able to work and deliver power but with a very low performance. For this project EOL of the battery is going to be used as the point at which the battery has undergone 20% capacity fading.

Energy Throughput

This is a measure of the total amount of energy that goes into as well as comes out of the battery. In other words it represents the energy usage of the battery. Total energy throughput is the total energy that passes through the battery throughout its lifetime.

2.2.4. Battery Costs and their importance

The overall battery cost that occurs in an off-grid PV system is the result of two different costs: the upfront costs and the lifetime-running costs. Battery costs can also be divided into these two categories. The upfront costs are directly related to the battery size. The larger the size of the battery is, the higher the upfront costs will be [€/kWh]. The lifetime-running costs, on the other hand, have to do with the lifetime of the battery. One of the main limitations of the storage units is that they have lower lifetime than the other components of the off-grid PV system. Thus, the batteries need to be replaced one or more times, depending on the technology, throughout the lifetime of the system. To sum up, upfront costs are expressed as a function of the battery size while running costs are expressed as a function of the replacements which are also depended on the battery size.

Furthermore, the sizing of the battery, also affects its lifetime. While increasing the battery size the average Depth of Discharge that the battery operates for a specific application is reduced resulting to different lifetime and therefore different upfront lifetime costs. Consequently, it is shown that the sizing of the storage also presents a trade-off between upfront cost and battery lifetime.

In general, different battery technologies have different costs as well as different advantages and disadvantages in terms of life-cycles. While lead-acid technology appears to have the lowest upfront cost, thus being the cheapest technology, it suffers from a very low battery lifetime. On the other hand Li-ion based technologies enjoy higher lifetime, thus need fewer replacements during the system lifetime but at the same time are more expensive in terms of upfront cost. Having this in mind this project aims to define the best trade-off between battery costs and lifetime in the specific application of SHS combining the best battery characteristics of different technologies in a Hybrid Battery. This battery will be considered the optimal storage configuration assessing the limitations of Solar Home Systems.

2.2.5. Factors Affecting Battery Selection in Specific applications

In general, in most applications a number of technical battery characteristics are considered in order for the optimal storage option to be chosen and used. However, the selection between the different battery storage technologies is becoming trivial due to an overlap between the different categories and parameters. More specifically, in some cases, the main considerations that are taken into account for the comparison of the different technologies are related to battery performance and battery life under different DOD and temperatures. In other cases the choice of the battery is location and application specific (PV system, Wind energy system, Hybrid System, EV, etc.) taking into account installation infrastructure, ambient conditions and space limitations. Lastly, cost as well as safety, are the common and main considerations concerning all types of applications and locations. Apart from the large number of factors that affect the choice of batteries the combination of cost and performance is very complex to be assessed and defined, while focusing on a single cost statistic might lead to non- profitable decisions [28]. This project aims to combine most of the battery lifetime, performance and cost characteristics in a single function making the procedure of choosing the most suitable battery technology as easier and as accurate as possible.

2.3. Battery Aging

Capacity and power fading occur in the battery due to many physical failure mechanisms that happen while the battery operates as well as in times when the battery does not undergo cycling. Different side reactions in the batteries can induce phenomena that will lead to battery aging and eventually failure, or sudden battery failure. These phenomena are cell cycling, short circuits and thermal runaway [29]**.**

2.3.1. Physical Aging Mechanisms of different technologies

Lithium-based Batteries

Capacity fading and aging of the battery are caused by many different internal mechanisms and are further induced by extreme temperatures and high charging-discharging rates. In lithium ion batteries the most critical aging procedures that are triggered by mechanical stresses and volume changes, occur in the negative electrode/electrolyte interface. Excessive growth of the passive layer and more specifically of the solid electrolyte interface (SEI) induces lithium corrosion and reduction of the power capability of the electrode, leading to power loss. In very severe cases these phenomena might lead to lithium plating that induces even further and more drastically the capacity fading of the battery. In addition, reactions at the positive interface might be induced at high temperatures and high SOC levels leading to oxidation of the electrolyte components, increase of the internal cell impedance and evolution of CO_2. All these affect the active cyclable material, removing a part of it and decreasing the battery capacity [30] [31] [32]. In terms of calendar aging, which is severe in Li-ion cells, the main mechanisms that take place causing capacity fading are the shift in the electrode balancing and low anode potentials that accelerate even further the loss of active lithium material [32].

Lead-Acid Batteries

For lead acid batteries, battery degradation is caused by many internal mechanisms as well. To begin with, anodic corrosion of grids, plate-lugs, posts or straps is considered one of main reasons for battery aging. Active mass degradation and loss of adherence to the grid which are the result of battery cycling reduce the available battery capacity. In addition, irreversible reactions such as crystallization or sulfation that form lead sulfate in the active mass of the material in combination with short circuits that are mainly caused due to deep discharge cycles, affect significantly the cycle life of lead-acid batteries. Lastly, when overcharging the battery or when there is a significant temperature increase as well as during self-discharge and electrolysis, loss of water is being observed affecting again the aging of the battery [33].

Nickel Metal-Cadmium Batteries

One of the most important characteristics of NiCd batteries in terms of cycle life is that the internal resistance remains more or less constant while the battery is cycling. This helps the increase of cycle life. Generally, the main aging mechanism that occurs in NiCd batteries is the progressive separator metallization that happens again when the battery is used. One very significant characteristic of all alkaline batteries is the "memory effect" at which is exhibited reduced discharge voltage at the end of discharge. The main cause of this effect is that the battery appears to remember the lower capacity level that was obtained during a shallow cycle, resulting to temporary loss of the maximum initial capacity. In terms of calendar aging Nickel-based batteries can be stored for a long period of time without having severe aging [18].

2.3.2. Battery Parameters and how they affect battery lifetime

2.3.2.1. Effect of Temperature

The way that the batteries perform in different temperatures and more specifically in extreme high and low temperatures is very important and especially in low cost applications such as Solar Home Systems as it is not economically feasible to apply temperature control. In general, batteries do have a high sensitivity at operating temperatures with some technologies being able to operate better at extreme temperatures and with others not as good. More specifically, the temperature has a double effect on the performance of the battery. While the temperature increases, the internal resistance of the battery decreases improving the battery efficiency and enhancing its energy capacity as shown in Figure 2-6. On the other hand, the increase of temperature triggers faster unwanted chemical reactions in the battery (The Arrhenius equation), causing irreversible damage on the components, capacity fading and decrease in the battery lifetime [25]. The lifetime sensitivity of different battery technologies on the temperature is shown in Figure 2-7 .

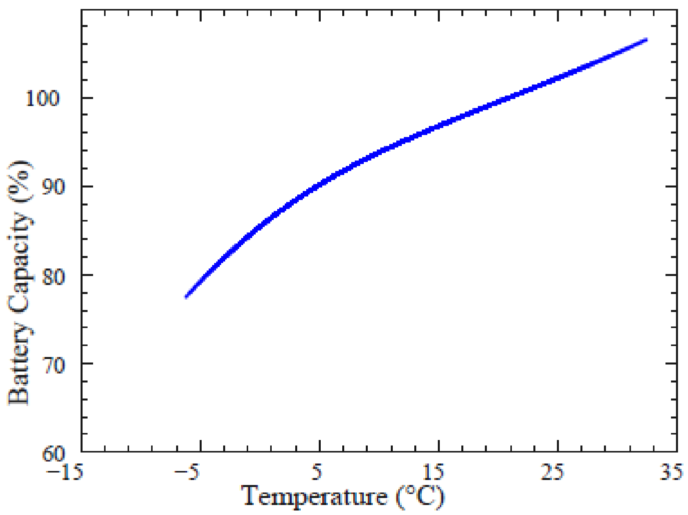


Figure 2-6: Positive effect of Temperature on battery capacity [as shown in [34]]

Arrhenius equation

The Arrhenius equation shows that the rate of the chemical reactions occurring in the battery has exponential dependency on the temperature as shown in Equation 2.6.

$$k = A \cdot \exp\frac{-E_a}{R \cdot T} \tag{2.6}$$

Where,
$\boldsymbol{A}$: pre-exponential factor
$\boldsymbol{k}$: rate constant,
$\boldsymbol{T}$: absolute temperature [K],
$\boldsymbol{E_a}$: activation energy [kJ/mol],
$\boldsymbol{R}$: universal gas constant [J/mol/K]

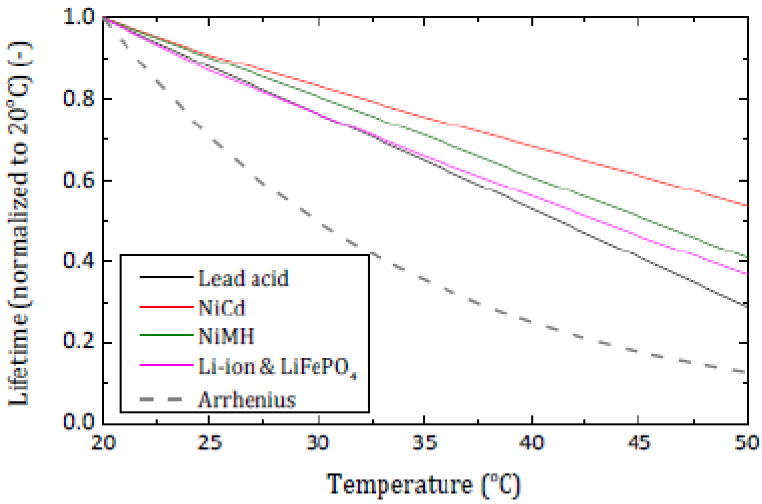


Figure 2-7: Effect of Temperature in battery lifetime for different battery technologies [as sown in [34]]

Temperature sensitivity of Lead Acid Batteries

For valve regulated as well as flooded lead-acid batteries the ideal operating temperature lays close to 20 ˚C - 25 ˚C, meaning that if the battery operates constantly at that temperature it will reach its maximum achievable cycle life. More specifically, when operating, lead acid batteries, it is recommended for the temperature to be in the range of -5 ˚C to 50 ˚C for discharging and in the range of 0 ˚C to 40 ˚C for charging. In addition, when lead-acid batteries are stored and not undergoing cycling, it is recommended for the stored temperature to lie between -15 ˚C to 40 ˚C [35]. Temperatures higher than 55 ˚C shorten the cycle lifetime of the battery drastically, though it is recommended from manufacturers not to operate at temperatures higher than 45 ˚C for a long period of time [36] [37].

Temperature sensitivity of Lithium-based Batteries

Lithium ion cells can safely be charged within 0-45 ˚C temperature range and discharged within -20 ˚C - 60 ˚C. These cells are more resistant to temperature, so that their capacity loss is not as easily affected in elevated temperatures as in Nickel-based cells. On the other hand, they experience higher capacity loss at low temperatures being able to deliver 90% of their maximum energy at 0 ˚C and 70 % at -20 ˚C. The ideal operating temperature range for Lithium ion cells lies between the range of 20 ˚C to 25 ˚C [38].

Temperature sensitivity of Nickel-based Batteries

For NiCd and NIMH batteries, manufacturers depict for 0-50 ˚C to be the maximum temperature operating limit and typically they even further restrict this range between 10-40 ˚C in conditions of fast battery charging. The best temperature level for these batteries is considered to be 25 ˚C. Above or below this “ideal” point the battery characteristics change significantly resulting to undesirable effects. These effects are capacity fading of the cell having as a consequence not be able to deliver the maximum energy when being fully charged. The second effect has to do with the ability of the cell to accept charge making the procedure of charging hard. This effect decreases the battery's charging efficiency, especially at temperatures higher than 40 ˚C. On the other hand, at low temperatures capacity fading is also observed but in a lesser extent than in high temperatures. In addition, low temperatures have as a result the reduction of the cell's tolerance at the maximum safe charging current mainly because the gas cannot recombine as easily inside the cell [38].

2.3.2.2. Effect of Depth of Discharge

In general, the dependency of the lifecycle of a battery is large on the depth of discharge at which the battery operates. While increasing the DOD of the battery, its lifetime is affected adversely, thus being decreased. The extent, to which the lifetime of the battery is increased, is different in different battery technologies [21]. Experimental results have shown that battery operation at small values of DOD improves the lifetime of the battery, decreasing capacity fading phenomena slowing down or preventing stresses that lead to irreversible damages [39]. Many manufacturer datasheets provide lifetime curves in respect to DOD. Some of them, for the battery technologies that are used in this report, are shown combined in a diagram in Figure 2-8.

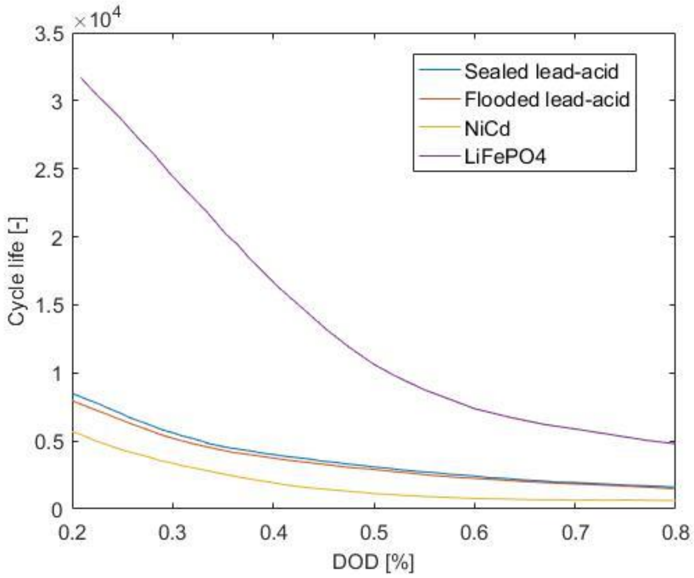


Figure 2-8: Reconstructed Cycle life curves in respect to DOD for different technologies as derived from manufacturer's datasheets [37] [36] [40] [41]

2.3.2.3. Effect of C-rate

Operating C-rate increases the cell temperature and internal Ohmic resistance increase as well. As it was mentioned before, the increase in the temperature has a negative effect in the battery lifetime, thus the increase in C-rate also decreases lifetime [42]. In general higher C-rates lead to higher capacity loss thus faster capacity fading and EOL [43].

In SHSs the operational battery current rate is very low reaching C-rates equal to 1/150C, thus it can be said that in such applications the C-rate is not taking a very active part in the battery aging process. In addition, the C-rate effect can be neglected, because it is not as severe as the effects of temperature and DOD/SOC in the battery lifetime [44].

In this study, the C-rate effects are also going to be neglected, as the temperature behavior of the battery was accounted by using battery datasheets which focus on the ambient temeprature and not the cell temperature. In addition many side chemical reactions are happening inside the cell as the cell temperature changes, which are very complex to be modeled and used for the battery lifetime.

2.3.3. **Battery Dynamic Modelling**

In general battery modelling can be distinguished in three different levels in terms of the physical insight that they provide as well as in terms of accuracy and complexity: white box, grey box and black box. An example of white box modelling is the electrochemical or physical models, an example of grey box modelling is the equivalent electrical circuit models and lastly an example of black box modelling is the artificial neural networks. These models need to satisfy specific criteria in order to be considered successful and suitable enough [45]. These criteria are:

- Accuracy, representing the extend which the model has achieved in imitating the behaviour of a real battery. In order for a model to be accurate enough, it has to match with experimental measurements taking into account the same battery parameters and external variables that the experiment considered. In addition, in order to be accurate a model needs to have a dynamic behaviour that has been tested and validated in the short as well as in the long run.

- Configuration effort represents the extend at which the chemical theory of the battery was used. This takes into account the number of chemical parameters and variables that were considered for the model and if they are enough to represent the battery in a satisfying degree.

- Computational complexity represents the time that the simulation needs in order to be completed. The smaller the time the better for the model.

- Analytical insight or interpret-ability represents whether or not the battery model was able to interpret the battery behaviour qualitatively enabling the design of battery management strategies and the exploring of performance and lifetime trade-offs [45] [46].

The battery behaviour can be modelled in many ways. The literature classifies the models in many different categories. The most common are the electrochemical or physical models, the equivalent circuit models, analytical or empirical models and Artificial Neural Networks (ANN). These types of models are going to be explained more analytically in Chapter section 4.2.

2.3.4. **Existing Battery Lifetime Models**

Experimental approaches, tried to observe and measure the battery degradation throughout time, semi-empirical approaches have represented the fade mechanisms using equations which fit specifically to a single battery chemistry and type of cell and lastly, theoretical approaches that have used the physics behind the side reactions to interpret the battery lifetime [31]. In most of these approaches, cycle and calendar fading were modelled taking into account temperature and time dependencies by combining Arrhenius equation and the rate of side reactions using a time relation that was conducted experimentally [47] [48].

It is worth pointing out that most of the studies and researches undertaken for battery lifetime are mainly for different types of lithium ion batteries because they have higher lifetime and they are being broadly used in electric vehicles. Most of these models have taken into account cycling aging and not calendar aging. This is mainly due to the time, calendar aging experiments require, even though the calendar aging phenomena could be accelerated by exposing the batteries in extreme temperature and charging conditions. Another reason that calendar fading hasn't been taken into account in many studies, is because it causes much less capacity fading than cycling phenomena cause to the battery. In the following section some of the already existing capacity fading models are explained.

A semi-empirical life model for lithium ion batteries that takes into account both calendar life and cycle life using data that were extracted from a cycle-test matrix was created by Wang et al.. This model used three battery parameters as stress factors to account for the battery degradation, temperature, time and discharge rate. For the inclusion of the calendar life the diffusion capacity loss is represented with a square root relation of time while the temperature effect is represented by an Arrhenius relation. The cycle life model was constructed by empirically fitting the capacity loss with a generalized exponential function that takes into account the rate effects [47].

Zabala et al. proposes a lifetime estimation method for LiFePO4 batteries taking into account calendar and cycling aging too. A comparison between the cycling aging of the battery, conducted through static tests (constant operating conditions), was compared with a dynamic battery degradation model. The battery parameters that are used for this capacity fading are DOD, C-rate and Ah-throughput. These parameters were all combined into a semi- empirical model for the aging prediction that was followed by a lifetime prognosis of the battery. The cycling aging was combined with calendar aging for the final lifetime estimation of the battery [49].

Dudezert et al. studied the battery aging applying a mechanical approach to the chemical processes that take place in the battery, connecting the stress factors that lead to battery degradation to the battery aging factors. The experiments were taken by exposing the battery in extreme stress conditions in order to accelerate the aging accordingly and reach to conclusions predicting the battery lifetime. The temperature effects were represented by the exponential term of the Arrhenius equation. The cycling aging was described by a variable called electrochemical fatigue damage that represents the physical active area evolution during the battery lifetime [50].

Many studies have used the rainflow method combined with Palmgren Miners' rule, which are going to be explained analytically in Chapter 4, in order to achieve battery lifetime estimation.

Tankari et al. in his study for combining ultracapitors and batteries aiming to achieve an efficient energy management in a Wind-Diesel Hybrid system, used rainflow counting method as well as Palmgren Miners' rule for the estimation of the battery lifetime. The fluctuating load he had from the wind production resulted for the battery to be cycled in micro-cycles or half cycles. The three point rainflow method that was used classified the individual charge and discharge cycles into 20 classes of equal size. Later on, a Miners' rule was applied by taking into account the cycling corresponding to DOD stresses that was extracted from rainflow, and a fitting equation corresponding to the cycling until the End-of-life for a specific stress, which was extracted from curves included in the manufacturer's datasheets. The End-of-life was set to be the point when the cumulative damage from the Miners' rule reached the unity [51].

Musallam et al. uses the rainflow algorithm for life consumption estimation, again combining it with Miners' rule. At the beginning, he applies the traditional method of rainflow counting in order to measure half and full cycles while later he develops a real time rainflow code for this algorithm. This new approach uses two flexible buffers and the number of full and half cycles is identified recursively while updating the life consumption models accordingly [52].

Dragisevic et al. uses the rainflow counting method in order to group and count cycles from fluctuating loading and then makes lifetime estimation for VRLA and Lithium ion batteries using fitting equations obtained through experiments. The stress factor for the rainflow algorithm in this study is also the DOD [53].

The main limitations of these different methods and modelling approaches is that they have been constructed for specific cells under certain temperature conditions and throughout a limited amount of time making them not accurate enough and not suitable to be used for other battery technologies. In addition, if some of these cells are going to be used in series or parallel for specific applications the modelling equations should be used as a combination more than one times for every cell.

In renewable energy applications, like Solar Home Systems everything needs to be examined in battery level and not in cell level, thus everything is modelled from a system point of view using different power managements schemes and not electrical models.

Chapter 3

Storage Sizing in SHS - Case Studies

This chapter introduces the different sets of PV-load profiles that are examined in this study and explains in detail the battery sizing methodology that was followed. The main goal of this chapter is to reach to the best Power management Architecture (between the two that are used) to move forward to the dynamic capacity fading model with, as well as the optimum battery size for the case studies used.

3.1. Introduction

The first step that needs to be taken for this project is the determination of an optimal sizing methodology. The most important factor for achieving a balanced optimal system sizing is to have the load profiles (LP) concerning the application that this project is dealing with (SHS).

3.2. Types of Load profiles - Case studies

The main kinds of usage consumption can be classified into three categories: Low, medium and high consumption usage. For these load profiles low power efficient appliances were used. For this project only two of these categories are going to be used as the case studies, low and medium load profiles with their corresponding PV power generation.

For the PV sizing of the two case studies a very simple algorithm was used that takes into account the number of Equivalent Sun hours in city Chennai in India as well as the average daily energy consumption of each one of the load cases. The decided PV sizes that were used will be presented below with their corresponding load profiles. After finding the suitable PV size of the different load profiles, the PV output was calculated following some steps which are summarized in the block diagram of Figure 3-1**.**

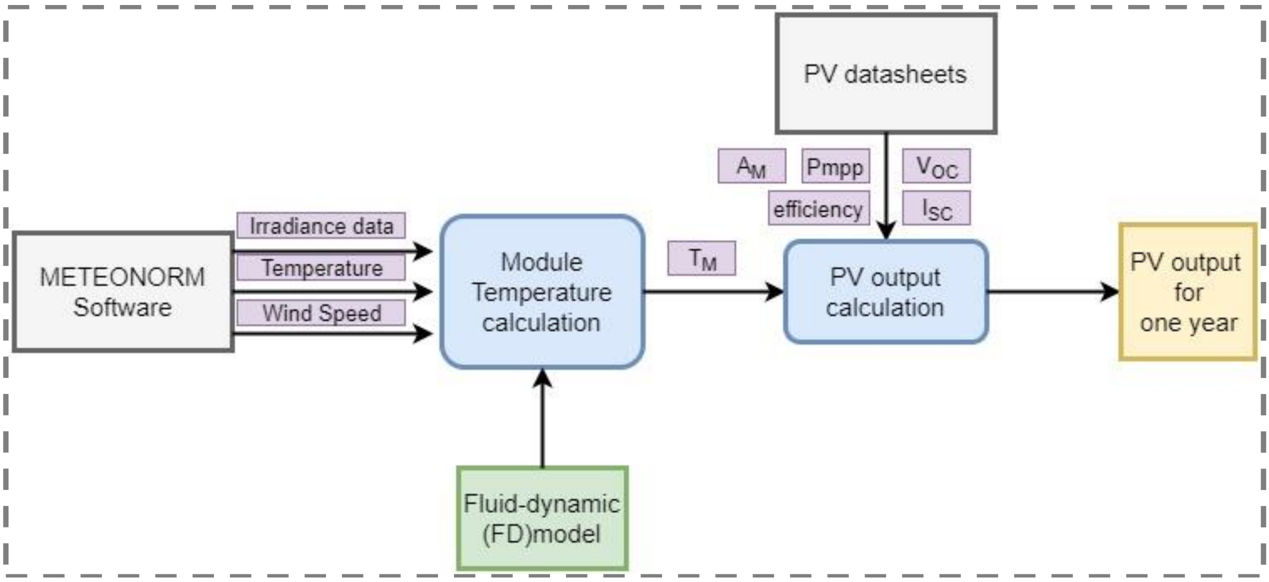


Figure 3-1: PV yield calculation procedure

The general PV output methodology as also shown in Figure 3-1 has as the first step the extraction of the location's ambient/ weather data. Temperature, irradiance and wind speed for one year were obtained from METEONORM software for the location of interest. The module orientation was set to be horizontal in order to examine the worst case scenario when sizing the battery in later steps and keep things as simple as possible. Using these data the Fluid-dynamic model (FD) was applied for the calculation of the module temperature. FD is a thermal model that is able to evaluate accurately the effects of important meteorological data concerning the location of interest creating a detailed energy balance between the module and the environmental aspects that surround it [22]. After calculating the operating temperature of the module, its effect on the module performance is expressed by different temperature coefficients of different parameters as extracted from the module datasheets. These parameters are open circuit voltage (V_{OC}), short circuit current (I_{SC}), efficiency (η) maximum power point power (P_{mpp}) and module area (A_M). These parameters were extracted from different manufacturer datasheets for the two PV sizes [54] [55]. Accounting all of the above the total output PV energy production can be calculated for one year. The load profiles as well as the PV profiles were given having a minutely resolution for one year.

3.2.1. Case Study 1 – Low power consumption load profile

In general, lighting, entertainment and communication, mechanical loads and labor-saving, food preservation, space cooling or heating, cooking and water heating, are the main categories consisting the basic human needs [56].

For the low power load profile, the appliances that were used are:

- LED lights
- Mobile phone
- Radio
- TV

A low power load profile for one day is shown in Figure 3-2. The calculation for the PV size for this load profile resulted to one panel of 40 Wp and its profile for one day is shown in Figure 3-3.

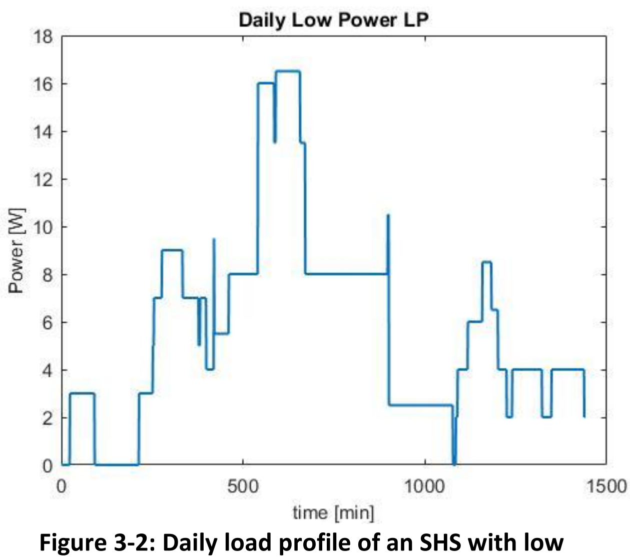


Figure 3-2: Daily load profile of an SHS with low consumption

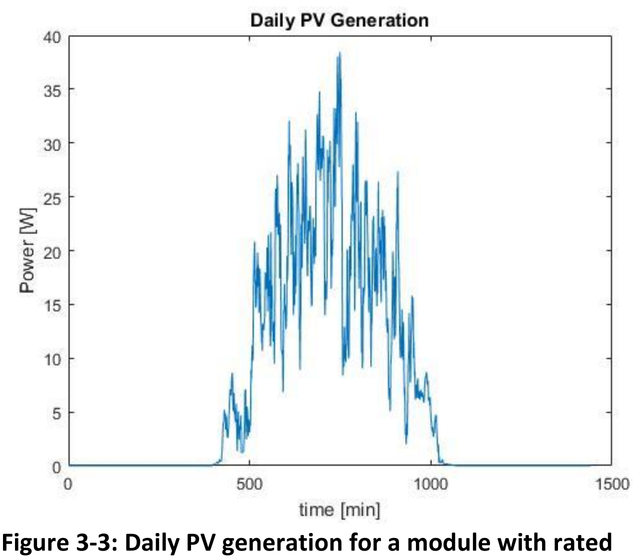


Figure 3-3: Daily PV generation for a module with rated power 40 Wp.

From Figure 3-2 it can be seen that in general the power consumption needed for this SHS system is very low and even when it peaks it is much lower than the average power value from the medium load profile as shown in Figure 3-4. It can also be seen that the peak in the power demand occurs very close to the midday when the PVs are going to be able to produce enough energy to satisfy the load, thus the battery needed, in this case is going to be small.

3.2.2. Case Study 2 – Medium power consumption load profile

For the medium power load profile, the appliances that were taken into account are the same as the low power case plus iron using efficient loads. A medium power load profile for three days is shown in Figure 3-4. The calculation for the PV size for this load profile resulted to one panel of 300 Wp and its profile is shown in Figure 3-5.

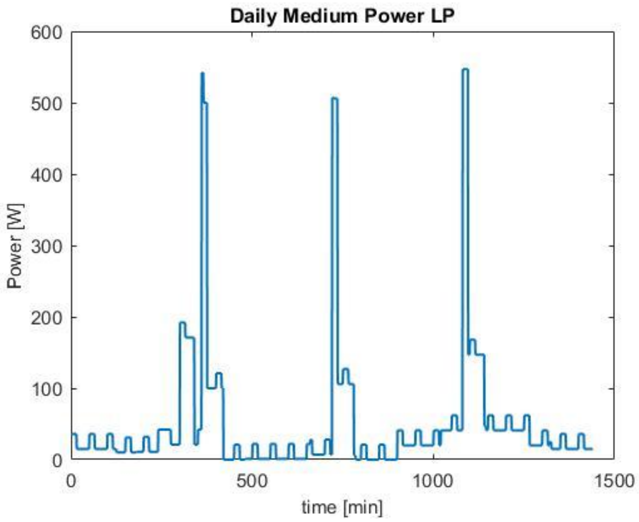


Figure 3-4: Daily load profile of an SHS with medium consumption

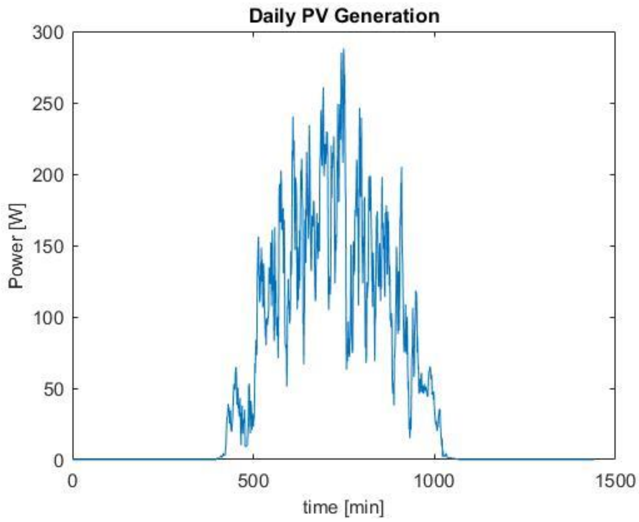


Figure 3-5: Daily PV generation for a module with rated power 300 Wp.

From Figure 3-4 it can be seen that the peaks in the power demand occur early in the morning, during the noon and late in the afternoon. In the morning and afternoon is clear from Figure 3-5 that the PV generation is almost zero thus energy storage is demanded in order to mitigate this difference. During the noon on the other hand, the energy demanded by the load can be satisfied by the generation of the PVs. The battery size needed in this case is going to be quite larger than the low consumption loads.

For the next steps such as lifetime estimation of the battery the temperature profile of the whole year also needs to be considered. The temperature profile with a minutely resolution for the city Chennai previously known as Madras in India is shown in Figure 3-6.

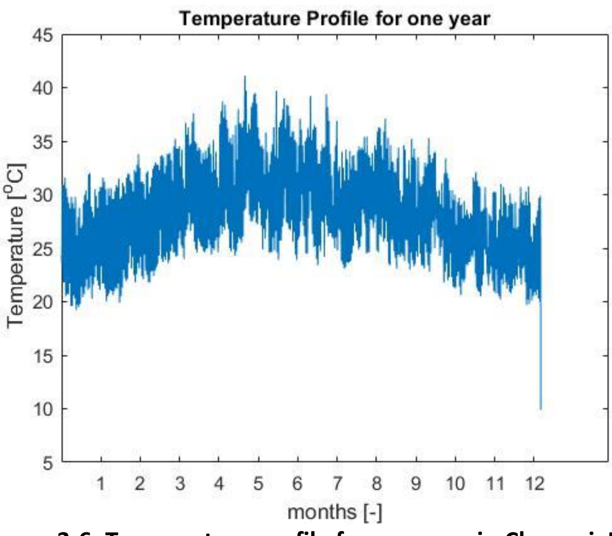


Figure 3-6: Temperature profile for one year in Chennai, India

From Figure 3-6 it can be seen that the temperature mostly varies between 20 ˚C and 40 ˚C. The minimum temperature value equals to 9.9 ˚C and is happening during the end of December while the maximum temperature equals to 41.1 ˚C and happens between April and May. Lastly, the average value of the temperature is 28.2 ˚C which is logical considering that South India lies in latitudes with high sunshine.

3.3. Sizing Methodology

One of the initial steps need to be taken is the optimal storage sizing for the specific load profiles that were considered in this project and described above. In order for this to happen a sizing methodology was followed. This methodology is going to be described and discussed in detail in the following sections.

3.3.1. **The Algorithm**

For the quantification of the storage size two different Architectures or otherwise system configurations that indicate the power flow in the system as well as battery usage, where used and compared. The exact net energy deficit and surplus of the battery were calculated at every minute for one year, which is the data resolution of the load profiles (525600 data), and the battery was charged and discharged accordingly depending on the Architecture that was used. The algorithm that was used for both Architectures was a Rule Based Energy Management algorithm that examines different cases at which the battery needs to be used (charged or discharged). A measure of the failure of the system was also used and evaluated at different battery sizes until reaching the optimal predetermined value. This measure is called Loss of Load Probability. The sizing of the battery was performed at MATLAB software.

Loss of Load Probability

The quantification of the storage size revolves around minimizing the Loss of Load Probability (LLP). LLP measures how many times the system, PV and battery contributions, failed to satisfy the load. The smaller this index is, the more reliable the system is. For example an LLP of 10% shows a 10% downtime of the system throughout the year which is translated to almost 36 days of system failure to satisfy the load. This is prone to happen on days with less sunshine, thus less PV production and high power demand. For the case of this model, after testing different numbers, the LLP was set as low as possible and not exactly equal to zero order to have a reasonable battery size and at the same time being able to minimize the failure of the system [22].

Efficiencies

For the sizing of the system, the battery efficiency was kept as a constant value without considering different battery technologies. The efficiency of the battery was set to be equal to 95%, a value that is very common for battery efficiencies at Solar Home Systems. The efficiencies were not considered dynamically with power or different for different technologies because the purpose of the sizing procedure, at this stage of the project is to simply and easily estimate a battery sizing considering the load cases that were given to us. Thus, the battery capacity that was found is a kWh value that mitigates the intermittency between energy generation and consumption accordingly to the used Architecture. The efficiency of the converter used for the sizing of the system was again kept constant and equal to 95%. In general the converters have very high efficiency, reaching levels of 98%. In renewable energy applications due to the fluctuation in the input power, the converter efficiency is varying between 80-98%. In order to keep things simple, the efficiency was kept constant.

Other Assumptions

For the sizing of the storage, capacity fading and aging mechanisms were not taken into account for this one year simulation. Temperature effects were also not considered, as they are going to be added with capacity fading later on in the battery lifetime estimation model. In addition, a limit for the DOD was set, equal to 80% meaning that the minimum capacity value at which the battery could be discharged was equal to 20% of the initial battery capacity. This assumption was made, in order to protect the battery from deep discharging and reduce its aging and capacity fading. This value is also considered appropriate and recommended by manufacturers. In addition the voltage of the batteries was kept constant to 12 V which is common for SHS applications [57].

Architecture 1

At the first architectural scenario the storage kicks-in only when there is a deficit of energy at the system, meaning that the battery is being used when the PV energy production is not enough to power the load, as shown in

Figure 3-7. This happens at times when there is not enough irradiation from the sun, thus not enough energy production from the PV panels to satisfy the high load demand.

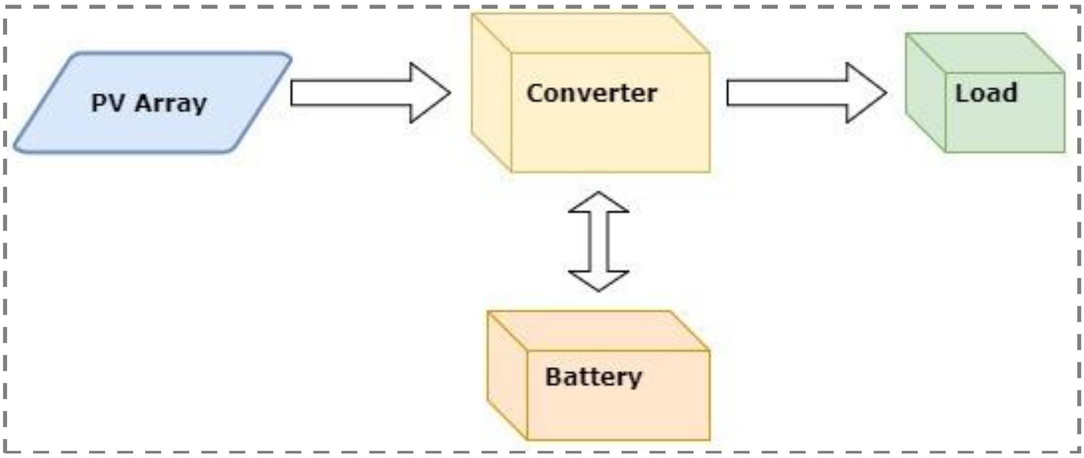


Figure 3-7: System configuration of Architecture 1

Architecture 2

At the second architectural scenario, the storage isolates the PV panels from the load as shown in Figure 3-8. More specifically after the energy is produced by the PV panels is fed directly to the battery. After that, the load demand is satisfied by taking the needed energy amount from the battery. Thus, the battery is cycled at every minute of the simulation as it represents the link between energy production and generation. Even though it is obvious that the battery usage in Architecture 2 will be much higher, resulting to much more battery cycling than Architecture 1, thus less battery life, this method was examined because this is a common phenomenon in developing countries. Small households own a battery unit that is moved and charged in a local kiosk and then used for the energy demands of the house, without having an energy production component such as PVs, etc.

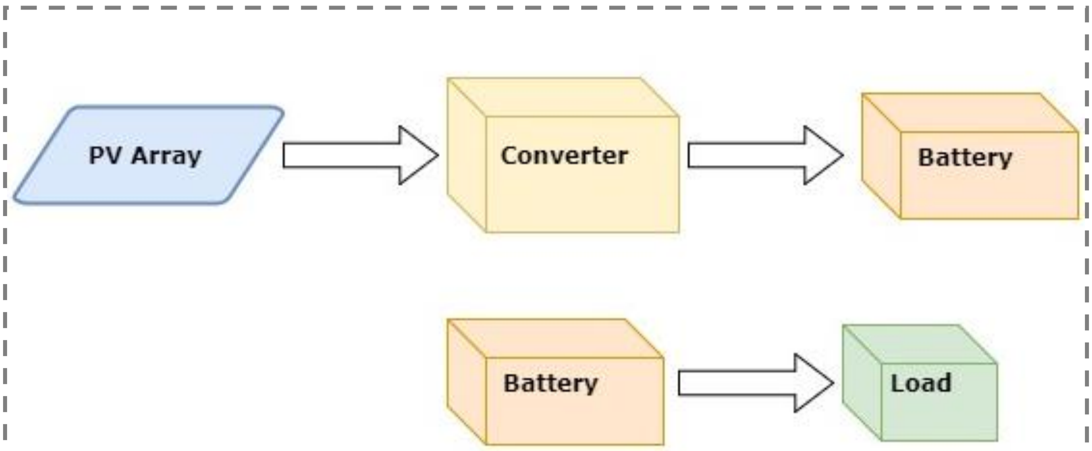


Figure 3-8: System Configuration of Architecture 2

3.4. Results

When applying low power load profile in Architecture 1 the battery sizing was varying in order to reach the optimum LLP levels that would give a reasonable battery sizing but at the same time being small enough in order for the system to be able to come through almost at all times. Due to the fact, that the low power load profile has very small energy demand the battery that used was also very small. In terms of comparing the different Architectures and decide which one is going to be used the LLP and energy throughput variation with the battery size were extracted from the simulation and compared. For both architectures and the two case studies, results for LLP minimization and energy throughput are shown below.

3.4.1. Case Study 1

The LLP that was set for this load-PV scenario is equal to 0.4%. Figure 3-9 and Figure 3-10 illustrate the LLP and energy throughput as calculated for different battery capacities for the two Architectures.

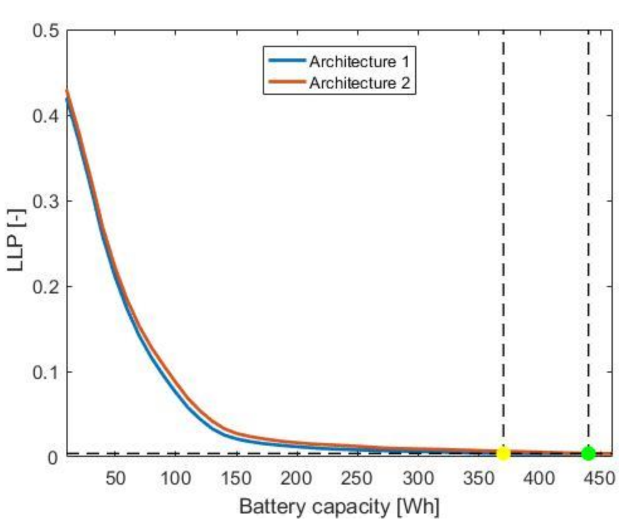


Figure 3-9: LLP for different battery capacities for low power LP.

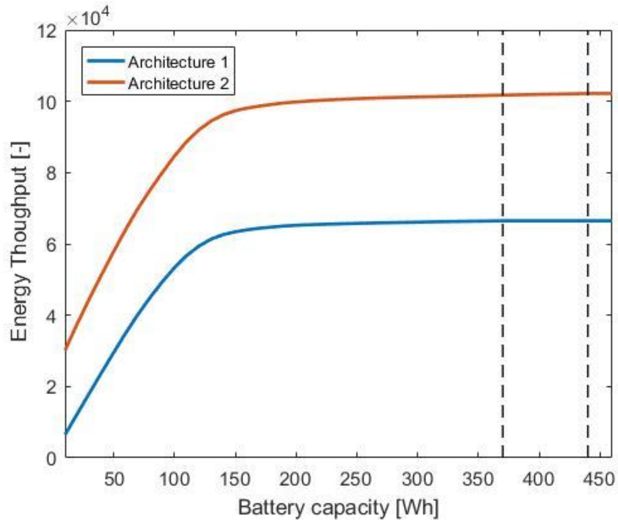


Figure 3-10: Energy throughput for different battery capacities for low power LP

The Loss of Load probability was set to be minimized at the value of 0.4% (very close to zero, translated to 1.5 days of system downtime throughout the year) which it is represented by the horizontal dashed line in Figure 3-9. In both Figure 3-9 and Figure 3-10 the two vertical dashed lines represent the optimum battery size that was reached for LLP equal to 0.4% for Architectures 1 (left vertical lines) and Architecture 2 (right vertical lines), respectively. In Figure 3-9 the intersection between the two LLP curves and the horizontal minimum LLP line, for Architecture 1 (blue curve) and 2 (red curve) are represented by the yellow and green dots, respectively. These points happen at 370 Wh and 440 Wh. It can be seen that Architecture 2 requires a bigger battery than Architecture 1. In addition, from Figure 3-10 it can be seen that the energy throughput in Architecture 2 is much higher than the energy throughput of the battery in Architecture 1, meaning that the battery will undergo much more cycling when the power management of Architecture 2 is applied, thus its lifetime will be shorter. The battery size decided for this case study equals to the best case scenario and is 370 Wh.

3.4.2. Case Study 2

The same methodology was again used, in order to determine the optimum battery size of the medium load scenario. The battery size was varied, and the minimum LLP was again set to be equal to 0.4%. The results extracted from the simulation are shown in Figure 3-11 and Figure 3-12.

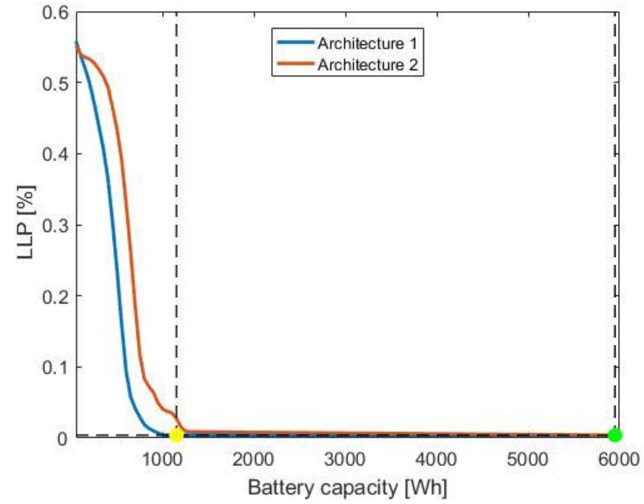


Figure 3-11: LLP for different battery capacities for medium power LP.

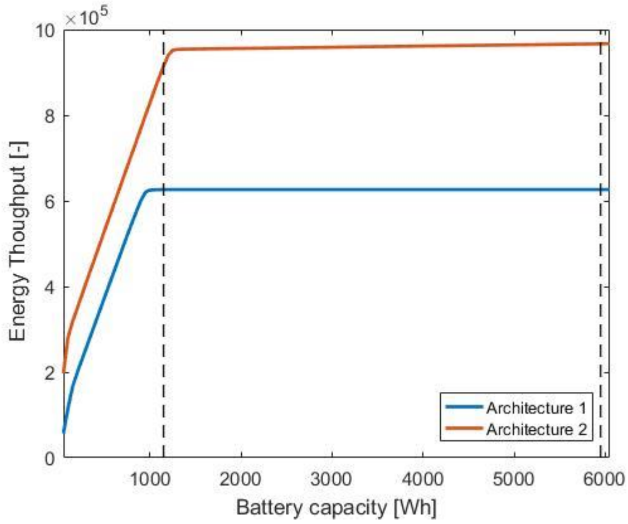


Figure 3-12: Energy throughput for different battery capacities for medium power LP

While it is again clear that Architecture 1 gives smaller battery size for LLP equal to 0.4%, it can be seen that the difference between battery sizes in two Architectures is too big. While, as shown in Figure 3-11, the minimum LLP value in Architecture 1 is being reached for battery capacity equal to 1150 Wh (yellow dot), in Architecture 2 is reached for 5950 Wh (green dot), almost five times the size required for the first Architecture. In addition, the cycling that the battery undergoes, as shown in Figure 3-12 using the second Architecture is much higher than using the first, meaning that the battery will die mush faster.

3.4.3. Conclusions

The main goal of this chapter was to determine the optimum battery size for each one of the load scenarios as well as decide the optimum Architecture, or otherwise power management configuration that gives the best results and is going to be used later for the next steps. The Architecture that gave the best results reaching the LLP limit in lower battery capacity and having the battery undergoing less cycling, for both case studies, is Architecture 1. The concluding sizing results for both Case studies are summarized in Table 2.

Table 2: Optimum battery size and energy throughput value for this size for both case studies

ARCHITECTURE 1		
Parameter	**Case study 1 (low LP)**	**Case study 2 (medium LP)**
Optimum Battery Size	370 Wh	1.15 kWh
Overall Energy Throughput	6.5×10^4	6.2×10^5 Wh

Chapter 4

Battery Lifetime Estimation

This chapter begins by introducing the different types of battery aging as well as different battery lifetime models. The main goal of this chapter is to introduce and explain step by step the non-empirical dynamic battery lifetime methodology proposed. During the construction of the model some intermediate results are shown helping to explain the choice of using specific methods instead of others. Lastly, the proposed methodology is applied for both case studies introduced in Chapter 3 and all four battery technologies of interest and validated with an empirical model. The lifetime results are analysed and discussed.

4.1. Introduction

As it was repeatedly mentioned before, battery lifetime is seen as one of the most vital parameters when designing a Solar Home System. For the estimation of the battery lifetime different battery parameters that affect it, need to be taken into account and combined dynamically. The interdependencies between the different battery parameters and aging mechanisms are very important to be modelled accurately. This study proposes a non-empirical dynamic battery lifetime estimation model that can be applied to different technologies, using stress factors as DOD and Temperature and capturing the different battery behaviours from the manufacturers datasheets.

4.2. Aging Models

Long term battery modelling can be expressed in many different ways such as battery state of health model, lifetime prediction model and battery aging or capacity degradation model. All of these models have as main goal to determine how long the battery can last before reaching obsolescence and how much irreversible damage has occurred in the battery throughout this time period. As it was already said before the End-of-Life of the battery happens when the battery has reached 80% of its rated initial capacity. The types of aging and the different lifetime prediction/capacity fading/aging model categories are explained in the following sections.

4.2.1. Types of Aging

Capacity fading is defined as the loss of discharged capacity at which the battery operates, over time. This capacity loss can occur in inactive times, when the battery does not undergo cycling or when it is stored and in times when the battery is exercised [27]. These two types of capacity fading are explained below.

Calendar Aging

Natural degradation of the battery occurs from aging and is directly connected with the temperature at which the battery operates or it is stored and in a lesser extend it is related to SOC of the battery. Throughout the years the battery loses a small percentage of its initial capacity due to aging.

Cycling aging

Cycle degradation occurs due to battery operation during charging and discharging cycles. It is strongly related to the temperature that the battery experiences during these cycles as well as the SOC/DOD of the battery.

4.2.2. Battery lifetime Modelling

Capacity fading models or lifetime prediction models that have as indication the determination of the SOH of the battery enabling the estimation of the battery lifetime and its long term behaviour can be divided into two different categories. The first one consists of performance based models and the second one of weighted Ah-throughput models or otherwise cycle counting models. Performance based models work simulating and observing the change in specific battery performance characteristics predetermining the EOL as a threshold (minimum) value. When the performance drops under this value then the battery has no further use. The monitored performance parameters can be the battery capacity, charge acceptance or discharge rate of the battery. This method needs to have as an input the rate that the battery degrades in order to know when it reaches EOL. The weighted Ah throughput models on the other hand, use predetermined parameter values such as the number of cycles that the battery can undergo throughout its lifetime, the Ah-throughput or the time since the battery was manufactured in order to be able to predict the time that the battery has reached EOL [52]. For this study the weighted throughput method was decided to be used as it is simpler and since it is not experimental the capacity fading rate of the battery was not known beforehand. Different performance based models as well as weighted throughput models are explained below.

- ***Performance Based Models***

These models have the ability to simulate battery performance taking into account the aging processes that occur in the battery throughout its lifetime. These models can be:

- **Electrochemical Models:** These, are the most complex and low speed models as they require extensive knowledge of the chemical as well as physical interaction of the batteries in order to be able to simulate in detail the battery conditions. Input information such as density, material porosity, volume of the electrolyte, etc. need to be given so that the determination of battery conditions such as temperature, electrolyte concentration, current, potential, etc. can be determined [44].
- **Equivalent Circuit Models:** For these models, the battery is represented by an equivalent electrical circuit with resistors, current and voltage sources, capacitors, etc. The prediction of the dynamic characteristics of the battery is the most common outcome from these types of models as the degradation and aging processes correspond to the changes of the values that are present at the equivalent circuit. These models cannot be used as lifetime prediction models as they are enable to capture stress factors as C-rate, DOD, etc. [44].
- **Analytical Models with empirical data fitting:** These models work by fitting and interpolating empirical data that have been obtained from actual experiments. The main challenges that these models have to overcome have to do with the amount of the data that is required as well as the way that they are going to link different battery stress parameters and combine their effect to the battery lifetime [44].
- **Artificial neural networks (ANN):** These models take as an input the operating conditions of the battery and have the ability to discover their relationship with the system outputs, which are the aging mechanisms of the battery. The in-depth understanding of the battery mechanisms is not necessary for the results to be obtained, but measurements need to be taken for this model to be conducted [44].

Damage accumulation model

The damage accumulation model is a performance based model that is used to simulate mechanical failure of an object and it is a summation of the damage that was observed in the object throughout its lifetime. This model uses the rate at which the damage has happened, thus the rate of the capacity fading of the battery. This rate is described in the following Equation 4.1 [44].

$$\frac{d\xi(t)}{dt} = \varphi(\xi, \sigma) \tag{4.1}$$

Where,

- $\boldsymbol{\xi}$: The amount of damage,
- $\boldsymbol{\varphi}$: Function of the damage ξ and the stress factor σ

- ***Weighted Ah-throughput models***

These models are mainly based on information given from battery manufactures, assuming that the battery is able to achieve an overall Ah-throughput or number of cycles throughout its lifetime, when operating under specific stress conditions (DOD, Temperature, C-rate, etc.). The main advantage of this method is that the deviations from the standard operating conditions can be observed as they affect (increasing or decreasing) the Ah-throughput for certain events, making the real-life battery simulation more accurate. Thus, these models are more appropriate for times that the battery is cycling with different DOD levels and in a variation of ambient temperatures. The limitation of these models is that this stress factor deviation from the standard conditions during battery operation needs be modelled accordingly and as accurately as possible. The End-of-life of the battery is reached when the total Ah-throughput or number of cycles that occur from the summation of all the events taken place during battery operation so far, reaches or exceeds the predetermined total lifecycle value [44].

Palmgren Miners' (PM) rule

One of the most common weighted Ah-throughput or counting cycle models, that counts mechanical aging or failure of a component is Palmgren Miners' rule. This rule is able to measure the fatigue of a component after it went through stresses and aging. It states that the lifetime of a component after undergoing a series of loads is reduced by a finite fraction corresponding to each one of these load events. This reduction fraction is the ratio between the number of cycles that the element has undergone under a particular stress factor divided with the number of cycles that the element was supposed perform until reaching EOL when operating continuously under this specific stress factor. This fraction is shown in the Equation 4.2. The End-of-life of the element is reached when the Damage (D), which is the cumulative of the fractions of life reduction, reaches the unity [44], [51].

$$D = \sum_{i=1}^{E} \frac{n_i}{N(\sigma_i)} = 1 \tag{4.2}$$

Where,

- $\boldsymbol{n_i}$: Number of cycles spent under a stress factor σ_i
- $\boldsymbol{N(\sigma_i)}$: Total Number of cycles for the EOL to be reached
- $\boldsymbol{E}$: Number of events taken place until the EOL condition is reached
- $\boldsymbol{D}$: Damage at the battery for each one of these events

The main difference between damage accumulation model and Palmgren Miners' rule is that for the first the damage rate needs to be known in order to be applied, while for the latter the entire development of the capacity fading until the battery reaches the EOL needs to be predetermined [58] . In this project Palmgren Miners' Rule is used, as the EOL conditions of the battery under specific stress have been extracted from manufacturer datasheets, for different technologies. In addition, damage accumulation model cannot easily be applied to the proposed model, because the rate of the damage for each technology is unknown and cannot be determined without conducting experiments on specific cells.

4.2.3. Important Characteristics of Battery Lifetime Models

Being able to predict the estimated lifetime of a specific battery technology or brand is very important especially when a selection of one battery for an application needs to be made. In order for the lifetime prediction model to be accurate enough it needs to satisfy specific requirements such as extensive knowledge of the aging processes that occur in the battery, the important stress factors that induce or accelerate the aging of the battery and how and to what extent these stress factors interact leading to battery damage. More specifically, a lifetime prediction model is required to consider specific parameters and follow specific characteristics that lead to some complexities. The main challenges that a lifetime prediction model needs to undertake and overcome and the main criteria that this model needs to satisfy are explained below:

1) The operating conditions of the application need to be considered for the lifetime estimation. These conditions might require the use of many stress factors that have to be combined together in order to simulate the aging process of the battery accurately. This procedure could be very complex as the effects of many of the aging mechanisms occur simultaneously.

2) Lifetime prediction needs to have predetermined threshold for the EOL of the battery. For this, it needs to be able to combine all the stress factors and aging effects of the battery into a single figure of merit (EOL) considering the severity of every stress factor to the aging process.

3) The lifetime prediction needs to examine the aging processes in battery level and not in cell level as it is going to be applied in a specific application. Thus, the effects need to be examined of the battery scope and not cell scope.

4) Lifetime prediction can only be useful if it is able to answer questions that have to do with application from user point of view such as: How long will a specific battery brand, (from a specific manufacturer) last when different applications and operating conditions are applied to it? How long will a new and more advanced with different material composition battery design last in a specific application?

5) The most important and complex challenge that a lifetime prediction model needs to overcome is the lack of lifetime related data availability by the different battery manufacturers. As it is expected, manufacturers are not able to test their batteries for a full range of different operating conditions or applications. For renewable energy systems there are very few complete datasets that give lifetime information and curves under different ambient conditions and stress factors. Thus, the biggest challenge of a lifetime prediction method is being able to predict the battery lifetime under conditions for which no lifetime tests were undertaken or even if they were they used non-similar conditions to the ones that the prediction is examining [59].

The dynamic capacity fading and lifetime prediction methodology that was constructed and followed in this study was able to overcome all of these challenges to satisfying degree thus, it is considered to be one of the unique contributions of this work. More specifically points 1 to 4 are satisfied completely while for point 5 some assumptions had to be taken. All these are going to be argued in detailed in the conclusions section of this chapter after explaining the followed methodology. The detailed methodology will be explained in the following sections.

4.3. Methodology

The lifetime estimation methodology that is followed in this study, is based in an idea that was conducted in the university for the IEEE Africon Conference [2]. After taking this idea, many layers of complexity were added to it in order to create a dynamic and a more accurate model for battery capacity fading and battery lifetime estimation. The methodology was validated while compared to an empirical model, adjusting it in the specific Solar Home System load cases used in this project. The following section explains thoroughly the methodology by presenting at the beginning the ideas used for the paper and step by step adding the different complexities until the full model is constructed.

4.3.1. Overall Lifetime Estimation Methods

This method consists of a simple lifetime estimation equation based on energy throughput and average DOD. The average DOD was calculated using three different methods in order to be as accurate as possible. These different methods are presented in the next section. The cycle life of the battery and first term of Equation 4.3 is calculated using a lookup fitting function (cycle life function) extracted from manufacturer datasheets. The third term of the equation indicates the total cycling that the battery undergoes throughout one year of simulation [2]. Thus, the battery lifetime is calculated by the following Equation 4.3.

$$\mathrm{L} = cl \times DOD_{avg} \times \frac{2 \times E_{nom}}{E_{thr,tot}} \tag{4.3}$$

Where,

- $\boldsymbol{L}$: the battery lifetime in years,
- $\boldsymbol{cl}$: the cycle life as calculated from the lookup function,
- $\boldsymbol{DOD_{avg}}$: the total average DOD,
- $\boldsymbol{E_{nom}}$: the nominal battery capacity,
- $\boldsymbol{E_{thr,tot}}$: the total energy throughput.

Cycle Life Function

Most battery manufactures provide in their datasheets a cycle life curve as a function of DOD. This curve indicates the maximum number of full cycles that a battery can undergo throughout its lifetime when operating at a constant DOD as shown in Figure 4-1. First, these curves were extracted from the battery datasheets for four technologies and a constant temperature, and a fitting lookup table was created for each one of these curves. This lookup table was approximated into a polynomial function that represents cycle life for a variation of DODs.

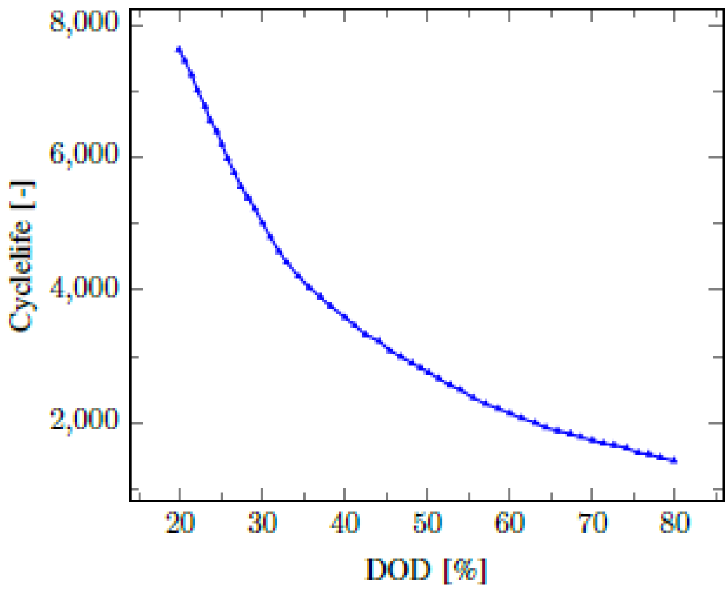


Figure 4-1: Reconstruction of battery cycle curve in respect to DOD for sealed lead-acid battery [as shown in [2]]

The polynomial function is a 4th order approximation that was applied for all different technologies used in this project. The following Equation 4.4 represents the cycle life approximation lookup function.

$$cl = p_4 \times d^4 + p_3 \times d^3 + p_2 \times d^2 + p_1 \times d + p_0 \tag{4.4}$$

Where,

- $\boldsymbol{cl}$: cycle life
- $\boldsymbol{p_0}$ **to** $\boldsymbol{p_4}$: fitting coefficients of the polynomial function,
- $\boldsymbol{d}$: DOD of the battery

This function as it is, is not taking into account temperature effects. As it has already been mentioned, temperature has a damaging effect on the cycle life of the battery. In order for the cycle life function to account for the battery temperature sensitivity too, another lookup function was constructed and used. Cycle life curves in respect to DOD for a variety of temperatures were extracted from the manufacturer datasheets. At this point it is worth pointing out that finding these curves for all the battery technologies examined in this report was a challenge consuming a lot of time and being a frustrating procedure. For some of the technologies, these curves were not able to be found for more than one temperature so they were normalized to that reference temperature by using the temperature linearity that the cycle life for these curves represents.

For VRLA (Sealed lead- acid) and flooded lead acid, the cycle life curves for different temperatures were found directly from the datasheets. For NiCd and LiFePO4 the curves were normalized to the reference temperature of 20 ^{o}C. More specifically through the investigation of NiCd battery, the datasheets found included only the cycle life curves for temperature equal to 20 ^{o}C. In addition, a curve representing the lifetime sensitivity on the temperature was also found as shown in Figure 4-4. In order to approximate the lifetime curves for 20-45 ^{o}C a constant ratio between the two cycle life-DOD curves was assumed for different ambient temperatures. For example, the reference curve of 20 ^{o}C was multiplied by 0.91 for 25 ^{o}C, by 0.84 for 30 ^{o}C, etc. The same procedure was followed for LiFePO4 batteries. The only difference is that the cycle life curve that was found was for 23 ^{o}C so it first had to be normalized to 20 ^{o}C and the reconstruct the curves for the other temperatures [60]. The reconstructed curves for VRLA and flooded lead acid batteries as derived directly from the datasheets are shown in Figure 4-2 and Figure 4-3 . The temperature sensitivity curves for NiCd and LiFePO4 are shown in Figure 4-4 and Figure 4-6 and their reconstructed cycle life curves for different temperatures are shown in Figure 4-5 and Figure 4-7, respectively. The method for normalizing and creating the different temperature curves was initially used in a SIP II project [60].

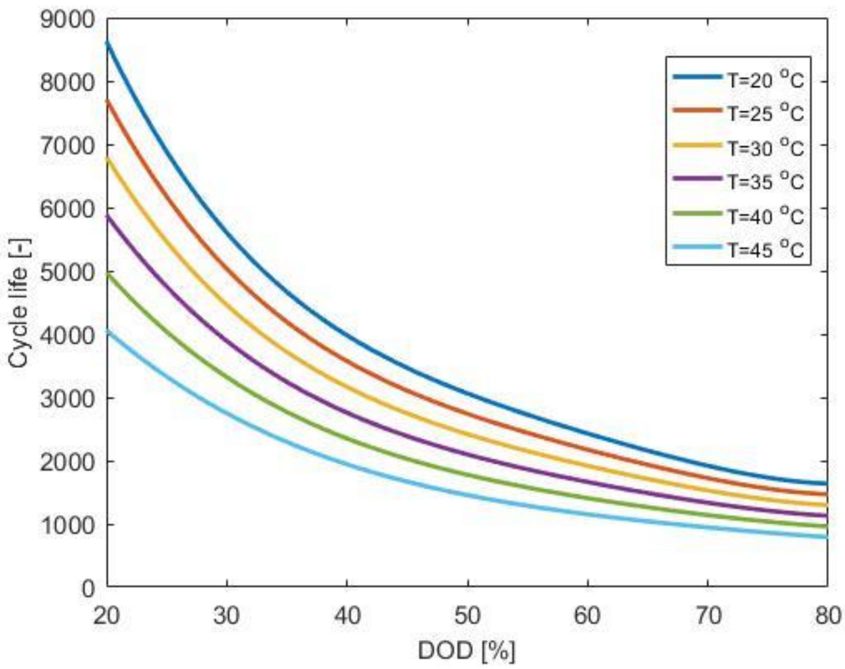


Figure 4-2: Reconstruction of battery cycle life curve in respect to DOD for different temperatures for sealed lead-acid battery [36]

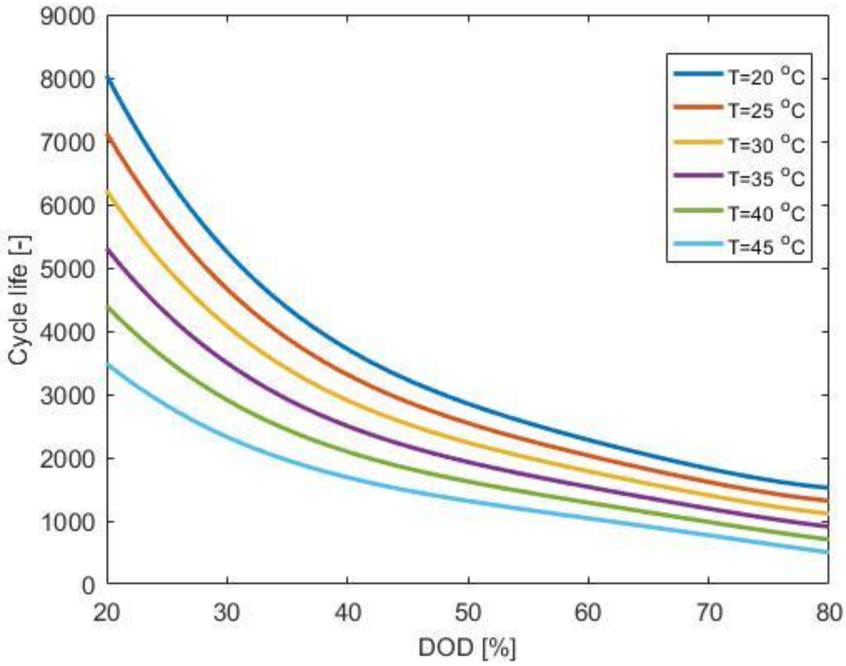


Figure 4-3: Reconstruction of battery cycle life curve in respect to DOD for different temperatures for flooded lead-acid battery [37]

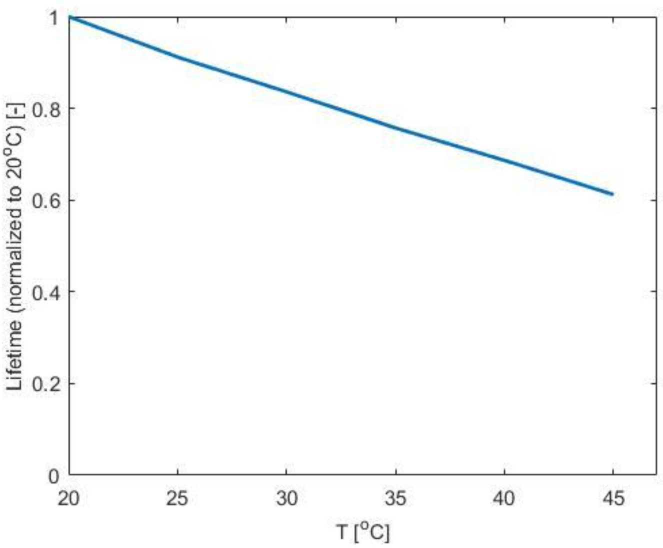


Figure 4-4:Temperature dependency of cycle life of NiCd batteries normalized to the reference temperature 20 °C [60] [61]

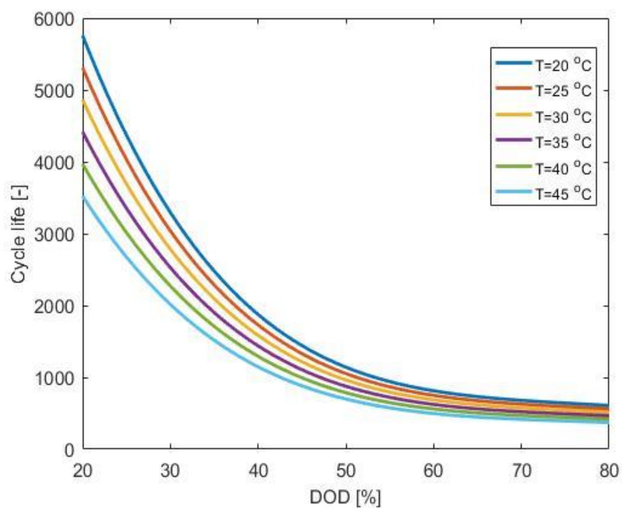


Figure 4-5: Reconstruction of battery cycle curve in respect to DOD for different temperatures for NiCd batteries [40]

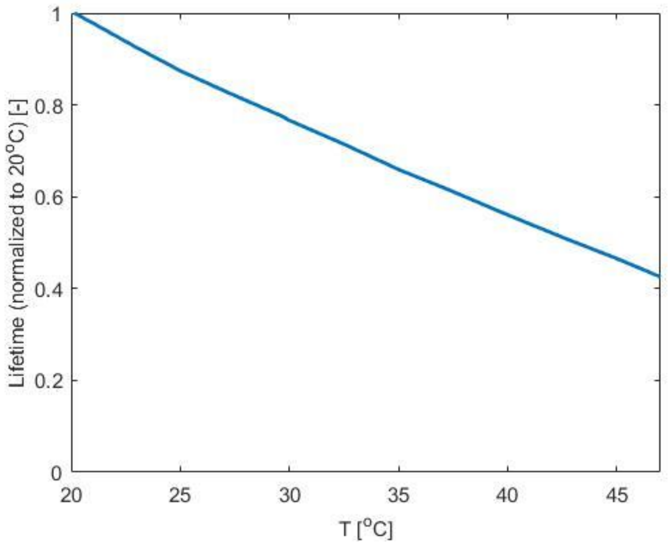


Figure 4-6: Temperature dependency of cycle life of LiFePO4 batteries normalized to the reference temperature 20 °C [60] [62]

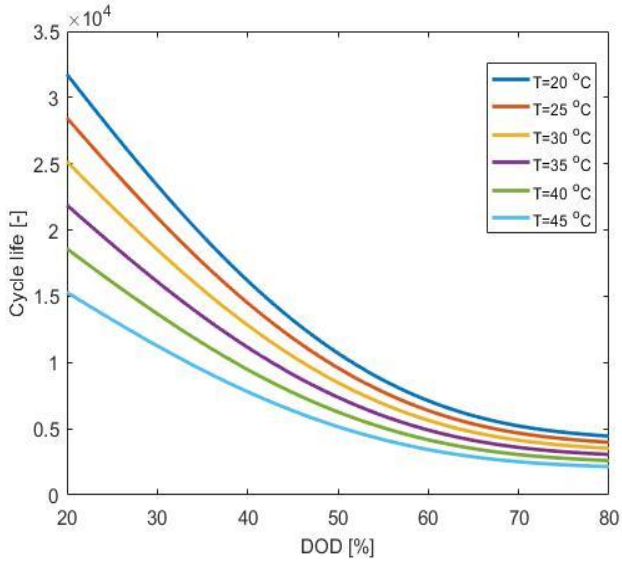


Figure 4-7: Reconstruction of battery cycle curve in respect to DOD for different temperatures for LiFePO4 batteries [41]

The polynomial function that was approximated taking into account DOD as well as Temperature effects, exploiting the linearity difference that cycle life presents in different temperatures is shown in the Equations 4.5 - 4.8.

$$cl = cl(T_{ref}) - f \times Dcl \tag{4.5}$$

Where,

$$cl\,(T_{ref}) = p_4 \times d^4 + p_3 \times d^3 + p_2 \times d^2 + p_1 \times d + p_0 \tag{4.6}$$

$$f = p_{lin_1} \times T_{avg} + p_{lin_0} \tag{4.7}$$

$$Dcl = p_{\mathrm{diff}_4} \times d^4 + p_{\mathrm{diff}_3} \times d^3 + p_{\mathrm{diff}_2} \times d^2 + p_{\mathrm{diff}_1} \times d + p_{\mathrm{diff}_0} \tag{4.8}$$

Where,

- $\boldsymbol{cl}$: cycle life of the battery
- $\boldsymbol{f}$: linear factor
- $\boldsymbol{Dcl}$: difference of cycle life between two temperature curves
- $\boldsymbol{p_0}$ **to** $\boldsymbol{p_4}$: the fitting coefficients of the polynomial function for the reference temperature,
- $\boldsymbol{p_{lin_0}}$ **and** $\boldsymbol{p_{lin_1}}$**:** the fitting coefficients of the linear difference approximated between the curves,
- $\boldsymbol{p_{diff_0}}$ **to** $\boldsymbol{p_{diff_4}}$**:** the fitting coefficients of the curve created when subtracting a temperature curve from the reference one,
- $\boldsymbol{T_{ref}}$**:** The reference temperature,
- $\boldsymbol{T_{avg}}$**:** The average operating temperature of the battery extracted from the simulation.
- $\boldsymbol{d}$**:** DOD of the battery

As it can be seen the cycle life equation approximated including the temperature effect in the cycle life of the battery is more complex that the one that does not. To begin with, a reference temperature is set for the cycle life curve which for most technologies is 20 ^{o}C. After subtracting the different temperature cycle curves, a linearity was observed between them and the reference curve, thus a linear factor was approximated as a linear function and the difference between any curve from the temperature as a 4th order polynomial lookup function. The linear factor is positive when the average operating temperature of the battery is lower than the reference temperature and negative when this temperature is higher. The coefficients of the cycle life lookup function for all the different technologies that were used are shown in Table 3 to Table 5.

Table 3: Fitting coefficients of the polynomial function for the reference Temperature (20 ^{o}C) for four battery technologies

Coefficients	Gel Lead acid	Flooded Lead acid	LiFePO4	NiCd
p_0	2.30E+04	2.08E+04	5.00E+04	1.57E+04
p_1	-1.12E+05	-9.83E+04	-7.03E+04	-7.14E+04
p_2	2.53E+05	2.13E+05	2.13E+05	-1.30E+05
p_3	-2.71E+05	-2.19E+05	3.09E+05	-1.03E+05
p_4	1.11E+05	8.66E+04	-1.56E+05	3.09E+04

Table 4: The fitting coefficients of the linear difference approximated between the curves for four battery technologies

Coefficients	Gel Lead acid	Flooded Lead acid	LiFePO4	NiCd
p_{lin_0}	-3.785774188	-3.911421039	-2.80769231	-3.33333333
p_{lin_1}	0.190763893	0.196177387	0.153846154	0.171111111

Table 5: The fitting coefficients of the curve created when subtracting a temperature curve from the reference one for four battery technologies

Coefficients	Gel Lead acid	Flooded Lead acid	LiFePO4	NiCd
p_{diff_0}	2.89E+03	2.45E+03	6.49E+03	1.42E+03
p_{diff_1}	-1.58E+04	-1.17E+04	-9.14E+03	-6.43E+03
p_{diff_2}	3.88E+04	2.54E+04	-1.69E+04	1.15E+04
p_{diff_3}	-4.44E+04	-2.64E+04	4.02E+04	-5.36E+04
p_{diff_4}	1.91E+04	1.07E+04	-2.03E+04	2.78E+03

4.3.2. Estimating Average DOD

Parameters such DOD, SOC and energy throughput of the battery were able to be extracted through the energy management simulation that explained in Chapter 3, using Architecture 1. The most important idea concerning the accuracy of the lifetime estimation method is the concept of active DOD/SOC. In general, the DOD/SOC that is being considered in lifetime estimation methods, consists of the DOD extracted throughout the overall simulation. However, it is important to make a distinction between the DODs at which the battery actually undergoes through cycling, thus being in active operation, and the DODs that happen in times that the battery is not cycling. These “inactive” periods, can be considered as the times that the battery lies at some DOD/SOC levels without being charged or discharged mostly times when it is full or empty. These time intervals when the battery is not in active operation are being excluded from the average calculations introducing the term active DOD/SOC. More specifically active DOD/SOC refers to the State-of-Charge or Depth-of-Discharge of the Battery, while it undergoes active cycling [2].

Having in mind the concept of active DOD/SOC three different overall methods for estimating the DOD values were conducted. Coarse estimation method, Zero crossings estimation method and fixed micro-cycles estimation method.

4.3.2.1. Coarse estimation method

The average DOD as well as the total energy throughput, were extracted by considering all the time periods, active and inactive for one year. The average DOD for the coarse lifetime estimation method is calculated as shown in Equation 4.9.

$$\overline{DOD} = \frac{\sum_{t=1}^{525600} \overline{DOD_t}}{525600} \tag{4.9}$$

Where,

- $\overline{\boldsymbol{DOD}}$: the average DOD,
- $\boldsymbol{t}$: the time (one minute resolution),
- $\boldsymbol{DOD_t}$: the DOD corresponding to every minute.

4.3.2.2. Zero-crossings based estimation method

While the coarse lifetime estimation method is enable to capture the operation of the battery accurately as it depends on the total average DOD of the battery, the zero-crossings method takes into account short and deep current cycles, by accounting all the micro-cycles that take place through the battery cycling.

ZCs micro-cycle

A micro-cycle is a small cycle of variable duration that exists between two consecutive current zero crossings [2]. *From now on we will be referring to this time interval as a ZCs micro-cycle.*

For this method all the zero current transitions in the one minute resolution data, were taken into account. The concept of zero crossings is explained more graphically through Figure 4-8. The average DOD is calculated by taking into account the average DODs through the non-zero intervals between the zero crossings, thus, using only the time periods when the battery actually undergoes cycling.

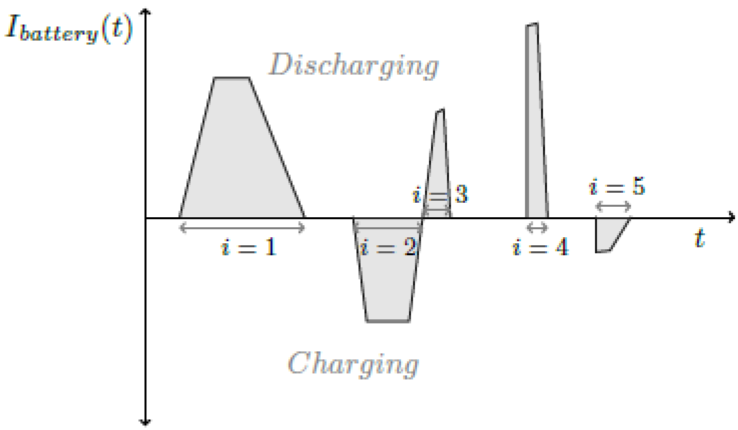


Figure 4-8: Illustration of the current intervals taken into account for the ZCs method [as shown in [2]]

While the lifetime is calculated by using the same equation that was used in the coarse lifetime estimation method with and without temperature effects (Equations 4.4, 4.5) the average DOD used in this method is calculated as follows.

$$\overline{DOD} = \frac{\sum_{i=1}^{N} \overline{DOD_i} \times E_{throughput_i}}{\sum_{i=1}^{N} E_{throughput_i}} \tag{4.10}$$

Where

- $\overline{\boldsymbol{DOD}}$**:** Combined average active DOD due to all the micro-cycles,
- $\overline{\boldsymbol{DOD_i}}$**:** Average active DOD in the i^{th} micro-cycle,
- $\boldsymbol{E_{throughput_i}}$**:** Total energy throughput in the i^{th} micro-cycle,
- $\boldsymbol{N}$**:** Number of micro-cycles throughout the year.

4.3.2.3. Fixed Micro-cycles estimation method

After considering the two aforementioned methods that were conducted for the conference paper the fixed-micro-cycle method was also used for the calculation of the average DOD approximation. This method takes into account fixed energy throughput intervals for the calculation of the average DOD that is going to be used in the lifetime equation method. Many tests were taken with energy throughput intervals starting from 10 Wh to 10000 Wh with a step equal to 10 as well as intervals equal to the optimum battery size or twice the value of the optimum battery size. The average DOD was calculated using the same equation as the zero crossing method uses (Equation 4.10) but the intervals were counted for the consumption of a fixed amount of energy throughput.

Comparing this fixed-micro-cycle method with the other two methods, it was observed that while the fixed Ah-throughput interval was increasing the closer the results were to the coarse battery lifetime estimation method. This observation makes sense and can be explained by the fact the coarse lifetime estimation method works as if it takes a huge interval over all the data points we have for the whole year (525600 points). Thus, the higher the interval is, the closer the fixed micro cycle method to the coarse estimation method is. In addition, when the Ah-throughput intervals were set to be non-constant but each time equal to the average value of the Energy throughput of the ZCs calculation intervals, the fixed-micro cycle method showed very similar estimation to the ZCs method, thus it was decided to not be used moving forward. All these observations are shown in Figure 4-9 when all of the methods were applied for yearly simulations and variable battery size.

Moving forward the fixed micro-cycle method is not going to be used as it was shown that it is validated only when the fixed intervals are equal to the ZCs average throughput intervals. Thus, ZCs and coarse lifetime estimation method are going to be analysed and compared in more depth.

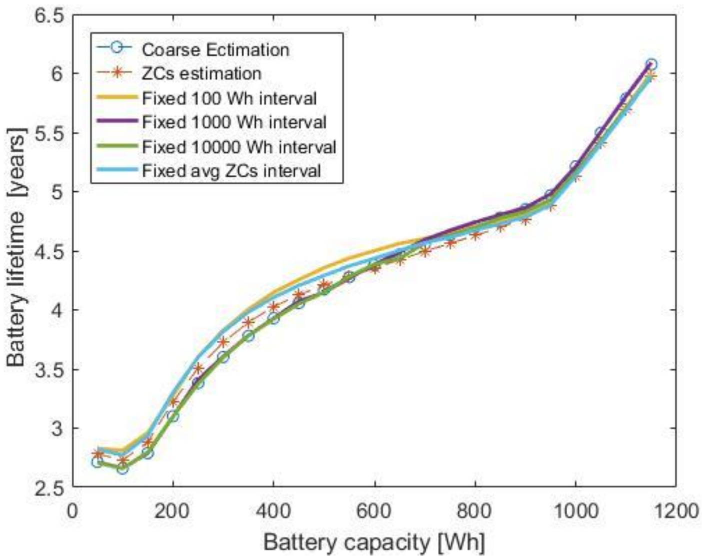


Figure 4-9: Comparison of lifetime estimation methods for variable battery size for sealed lead-acid battery. The fixed micro-cycle method was used with varied fixed Ah-throughput interval and is being represented by the normal lines

4.3.2.4. Overall lifetime estimation Results

- ***Testing and Comparison of Methods***

The comparison of the three different lifetime estimation methods was made by considering one of the load cases that were mentioned in Chapter 2. Case study 2 consisting of medium power load profile and a 300Wp PV panel, using Architecture 1, and optimum battery size 1.15 kWh, as described in Chapter 3, was simulated for one year on MATLAB. After the yearly simulation, the methodologies of coarse lifetime estimation, ZCs lifetime estimation and fixed micro-cycles lifetime estimation were applied using Equations 4.9 for the first and 4.10 for the two others, in order to determine the different average DODs to be used. Lastly using Equation 4.3 in combination with Equation 4.4, the lifetime of the battery was calculated. This methodology was applied for the optimum battery size as well as for a variation of different battery sizes in order to examine how the lifetime of the battery changes with the battery sizing.

First, a comparison between the two DOD estimation methods, coarse and ZCs is done without the use of temperature effects (the two methods used for the conference) in order to decide which one is the most accurate and is going to be used for the next steps. Figure 4-10 shows a histogram of the different DOD levels that the battery experiences throughout one year including active and inactive battery periods as well. However Figure 4-11 shows only the active DOD levels that the battery experiences during this year, as being measured with the ZCs estimation method.

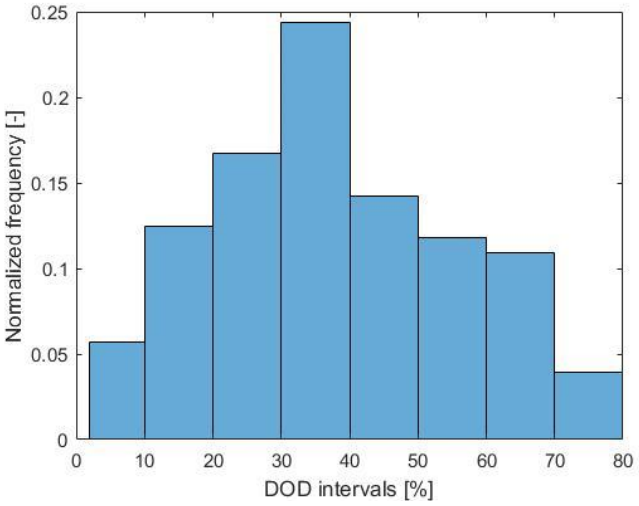


Figure 4-10: Histogram for DOD value used for coarse lifetime method [2]

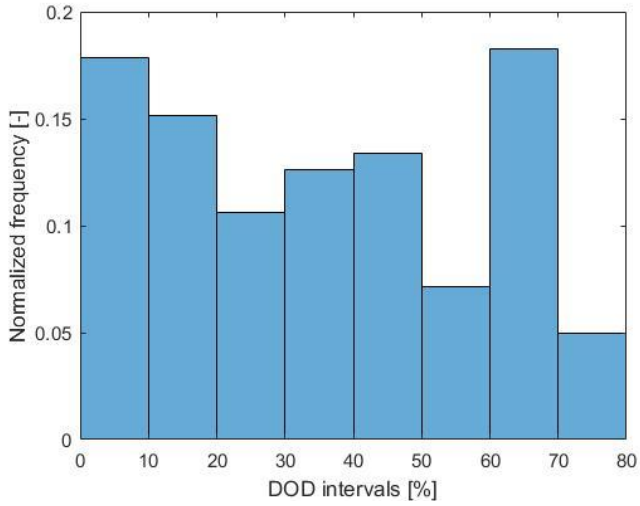


Figure 4-11: Histogram showing only active DOD values as used in ZCs method [2]

The differences between these two histograms have to do with the fact that Figure 4-10 includes all the inactive periods of the battery as well as the active ones. It is worth pointing out that the DODs with values between 0 - 0.02 were excluded from this figure because it was very disproportionate otherwise, as they represent all the times that the battery was full and inactive. The average DOD values that were calculated for both methods coarse and ZCs are presented in Table 6.

Table 6: Average DOD values over a simulation of one year with two different methods

Parameter	Value [-]
Average DOD	0.33
Average active DOD (ZCs)	0.36

As can be observed from Table 6 there is significant difference between the overall average DOD values obtained from the coarse method and the active DOD value obtained from the ZCs method. The overall average DOD is lower than the active one, thus coarse estimation it is considered to be a more optimistic method for battery lifetime.

- ***Observation of how battery size affects battery lifetime***

These estimation methods were also applied for variable battery sizing in order observe and extract some conclusions of how the battery sizing affects the lifetime of the battery. This application is shown in Figure 4-12.

The general trend that is followed in Figure 4-12 is that while the size of the battery increases the lifetime of the battery decreases. And this is logical because as the battery is bigger the variation of DOD is smaller having smaller average values as well, thus higher lifetime. In other words, in larger sizes the battery does not undergo deep charge-discharge cycles avoiding extensive fatigue. However, between the vertical dashed lines in the figure a weird curve is observed showing smaller battery sizes to have higher cycle life than larger battery sizes. An explanation for that is that at lower capacities between these size intervals there are more times that the battery fails to meet the load. In these time periods the battery lies empty and does not undergoing cycling. On the other hand, while going to higher capacities the battery is able to cycle more and this extra number of cycles are considered and added at the overall battery lifetime leading to smaller lifetime in the end. The main conclusion is that the battery lifetime curve in terms of sizing is depended on the load profile and more specifically at the usage thus the cycling that the battery undergoes for specific PV-load cases.

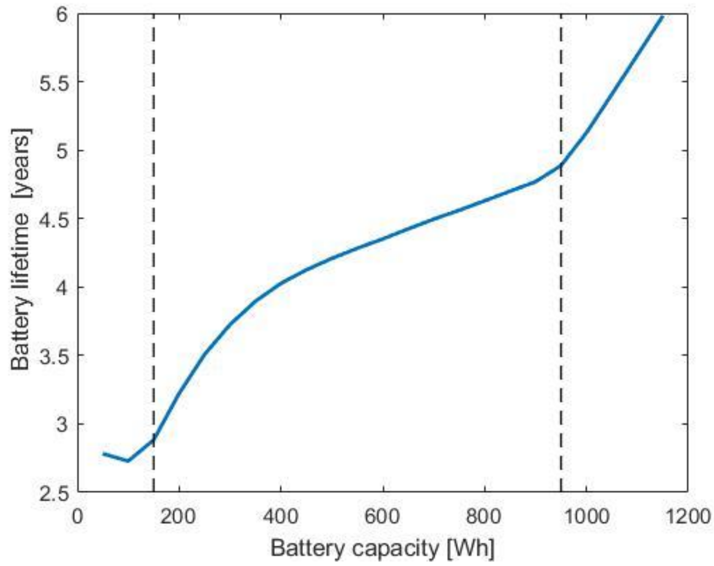


Figure 4-12: Sealed lead-acid battery lifetime calculated from ZCs estimation method for variable battery sizes

- ***Validation of ZCs method***

In order for the zero crossings lifetime estimation method to be validated and have a meaningful comparison, an empirical model was adopted to the specific Solar Home System Model used in this report for Lithium Iron Phosphate batteries and Case study 2. The empirical model uses capacity fading equations for describing the degradation and aging mechanisms of LiFePO4 battery [63]. This model was also contacted at the university. The equations that the empirical model uses, and were adopted in the SHS model for the comparison are:

$$c_f = \sum_i^E \left(\left(k_{s_1} SOC_{dev,i} . e^{k_{s_2} . SOC_{avg,i}} + k_{s_3} . e^{k_{s_4} . SOC_{den,i}} \right) . e^{\left(-\frac{E_g}{R}\left(\frac{1}{T_i} - \frac{1}{T_{ref}}\right)\right)} \right) . Ah_i \quad (4.11)$$

$$SOC_{dev} = \sqrt{\frac{3}{\Delta Ah_m} \int_{Ah_{m-1}}^{Ah_m} \left(SOC(Ah) - SOC_{avg} \right)^2 . dAh} \quad (4.12)$$

Where

- $\boldsymbol{cf}$: the capacity fading experienced by the battery,
- $\boldsymbol{i}$**:** is an event or arbitrary length of time,
- $\boldsymbol{E}$: the total number of events taking place throughout the simulation,
- $\boldsymbol{Ah_i}$: the total charge processed through an event I,
- $\boldsymbol{k_{s1}}$ **to** $\boldsymbol{k_{s4}}$**:** are the experimentally determined constants
- $\boldsymbol{SOC_{dev}}$**:** is the normalized standard deviation from SOC_{avg} in an event.

For the comparison of the ZCs and coarse lifetime estimation methods to the empirical model, the temperature was kept constant, thus the last exponential temperature factor in Equation 4.11 was set to be equal to unity. The lifetime results for LiFePO4 batteries of the two methods are shown in Table 7.

Table 7: Comparison of the empirical model to ZCs and coarse lifetime estimation method

	Empirical Model	**Coarse lifetime estimation**	**ZCs lifetime estimation**
Lifetime [years]	22.88	24.28	23.77
Deviation from empirical model	-	6.1 %	3.8 %

The lifetime results show that the ZCs method deviates from the empirical model by less than 4% while the coarse method deviates from the empirical model by almost 6%. The main conclusion is that the ZCs estimation is more accurate than the coarse lifetime estimation method, as it takes into account the actual cycling of the battery, the times that the battery is really active. The ZCs method is the one that is going to be used forward for the estimation time intervals to be considered for the DOD values.

- ***Temperature effect validation***

All of the above results were not considering the temperature effects. In order to compare whether or not the temperature plays an important role to the cycle life function, the cycle life of the battery using Equation 4.4 that does not include temperature and the cycle life of the battery using Equations 4.5-4.8 that include temperature effects, was calculated and illustrated for variable battery sizes. The different cycle lives were applied to Equation 4.3 calculating the lifetime of the battery in years. This is in shown in Figure 4-13. It can indeed be seen that the lifetime of the battery including the effect of the temperature is shorter than when this is not the case.

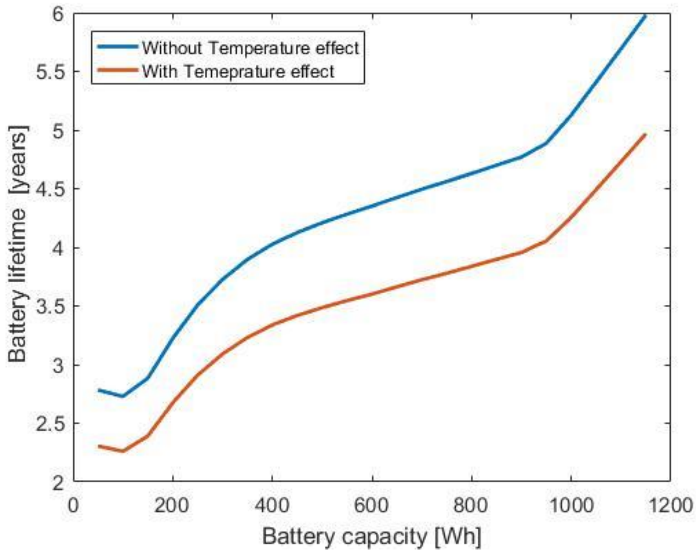


Figure 4-13: Sealed lead-acid battery lifetime comparison with and without Temperature inclusion

- ***Lifetime results for different Technologies***

The lifetime results of different battery technologies conducted by applying ZCs lifetime estimation method including temperature for one year of simulation for optimum battery size for Case studies 1 and 2 are shown in Table 8 and Table 9.

Table 8: Battery lifetime for different Technologies for low power LP (optimum battery size=370 Wh)

Battery Technology	Cycle life [number of cycles]	Cycle life [years]
Sealed lead-acid	7.79e+03	15.67
Flooded lead-acid	7.16e+03	14.39
NiCd	5.59e+03	11.22
LiFePO4	2.78e+04	55.82

Table 9: Battery lifetime for different Technologies for medium power LP (optimum battery size=1150 Wh)

Battery Technology	Cycle life [number of cycles]	Cycle life [years]
Sealed lead-acid	3.76e+03	4.97
Flooded lead-acid	3.46e+03	4.57
NiCd	2.04e+03	2.70
LiFePO4	1.57e+04	20.70

When comparing the different battery technologies, a general trend is shown in both Case studies. Lithium Iron Phosphate batteries (LiFePO4), exhibit the higher lifetime, having a big difference from the other technologies. Lead Acid batteries present similar lifetime between them, with flooded having a little bit shorter lifetime than sealed lead acid. Lastly NiCd batteries show the shortest lifetime of all the technologies.

When comparing different Case studies it is clear that the lifetime of the battery is very increased in low power LP compared to medium power LP. This happens because the battery undergoes a lot less stress in the low LP case as there are not so many peaks, thus not as many as deep charging and discharging cycles as in Case study 2.

4.3.3. Non-empirical dynamic battery lifetime estimation method

Even though the overall lifetime estimation methodology was validated, it still is enable to capture the real battery behaviour as it is using yearly average values. In real battery operation, this is not the case. The battery degrades dynamically and gradually over its lifetime. This battery behaviour was tried to captured and modelled.

The methodology that was followed for the construction of the dynamic battery lifetime estimation method consists of dynamic capacity fading that is modelled by multiple stages. A simple illustration of the steps followed and the methods included for the dynamic capacity fading is shown in Figure 4-18**.** First, a cycle counting method in combination with a fatigue estimation method as found from the literature and adopted to the model are going to be explained showing some intermediate results. Later the overall methodology will be discussed thoroughly.

4.3.3.1. Rainflow Counting Algorithm

This method is broadly used for the analysis of fatigue data allowing the application of Palmgren Miners' (PM) rule for the assessment of the damage that was caused in the battery. The main function of this algorithm is to reduce the number of cycles that happened during an event into groups of cycles that experience the same stress. The number of groups is given by the user and is otherwise called bin number, representing the number of classes that you wish to divide the stress profile. The first step is to apply a stress profile over time to the algorithm. This load profile is given as an input to the rainflow counting algorithm, which finds the peaks and valley from this stress-time signal and generates full and half cycles with the same stress. Once the cycles are counted, another subroutine is used to create histograms that show the frequency of each stress in number of cycles. The stress factors that were used for this project are DOD and temperature. Using this method we minimize the total amount of data that need to be analysed for every event and PM rule can easily be applied at a later stage in order to calculate the total damage occurred during a specific event [52]. A representation of how the rainflow algorithm works is shown in Figure 4-14**.** It can be seen that full and half cycles are taken into account by finding the peaks and valleys in the DOD profile signal given.

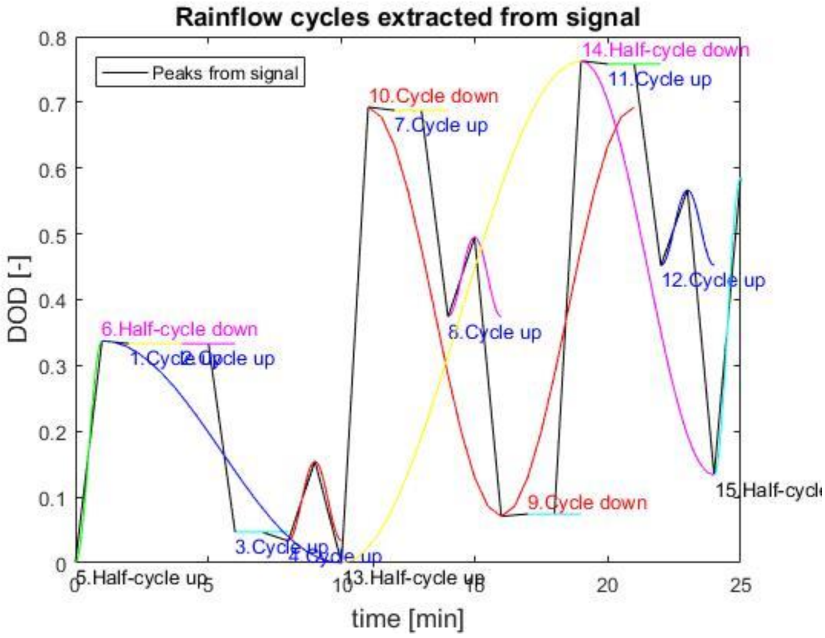


Figure 4-14: Rainflow Counting algorithm for cycle extraction applied to a 3 day DOD profile extracted from the simulation [64]

In order to be able to show in more detail how the rainflow algorithm works in combination with PM rule, some intermediated results were extracted from the simulation and shown below. To begin with, the simulation was run for one year, using medium load profile (Case study 2) and the DOD variation of the battery for the whole year was extracted in a minutely resolution. This DOD profile (Figure 4-15) was fed to the rainflow algorithm function. This function was adopted from MathWorks, written by Adam Nielson and changed accordingly in order to be able to fit to the dynamic capacity fading code [64]. After feeding this load profile to the rainflow function and set the bin number, for now 10, the number of cycles with specific stress is counted and grouped, as well as the total number of full cycles is calculated. This cycle frequency for the one year simulation is illustrated by a histogram as shown in Figure 4-16 and the detailed results are shown in Table 10**.**

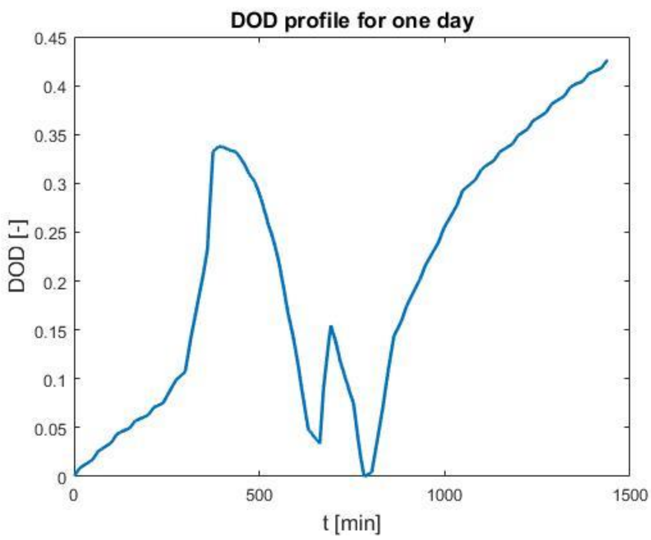


Figure 4-15: Daily DOD profile as extracted from one year of simulation

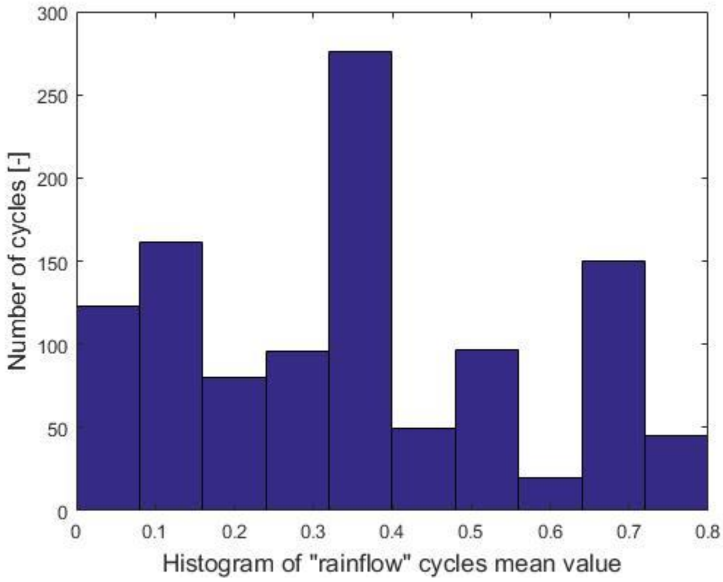


Figure 4-16: Histogram expressing the frequency of the cycling the battery has undergone for specific stresses, grouped in ten bins, for one year of simulation

Table 10: Results of grouped cycles from rainflow algorithm with their corresponding stress for one year of simulation

Group Number	DOD variation (stress)	Full Cycles (n)	Cycles until EOL (N)
1	0.0400	123	1.8910 e+04
2	0.1200	161	1.2720 e+04
3	0.2000	80	0.8650 e+04
4	0.2800	96	0.6087 e+04
5	0.3600	276	0.4524 e+04
6	0.4400	49	0.3568 e+04
7	0.5200	97	0.2931 e+04
8	0.6000	20	0.2436 e+04
9	0.6800	150	0.2015 e+04
10	0.7600	45	0.1708 e+04
Total Number of Cycles		1097	-

When applying Palmgren Miners' rule the numerator of the damage fraction represents the number of cycles (n) for a specific stress (DOD) as extracted from the rainflow algorithm (3rd column of Table 10), while the denominator is the number of cycles that correspond to the same stress until the battery reaches EOL, as extracted from manufacturer datasheets (N) (4th column of Table 10). Figure 4-17 shows the reconstructed cycle life curve of the sealed lead acid battery used in this study, and the projection lines show the DOD stresses and their corresponding cycle life that was used in PM rule. The cycle life values illustrated by the projection curves in this figure are the values shown in the last column of Table 10.

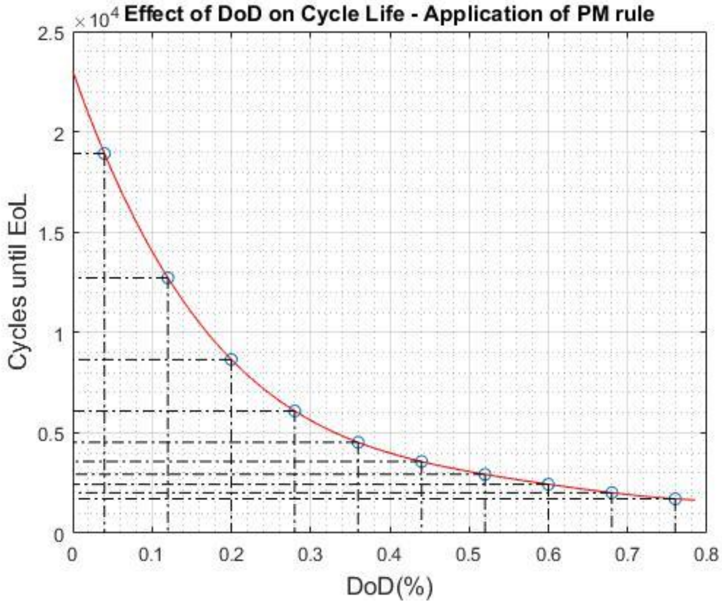


Figure 4-17: Stresses extracted from rainflow algorithm and their corresponding End-of-life cycle number for Sealed lead acid battery

The cumulative Damage for the one year simulation is calculated as follows:

$$D = \sum_{i=1}^{10} \frac{n_i}{N(\sigma_i)} = \frac{n_1}{N(0.04)} + \frac{n_2}{N(0.12)} + \frac{n_3}{N(0.20)} + \cdots + \frac{n_{10}}{N(0.28)} \\ = \frac{123}{18910} + \frac{161}{12720} + \frac{80}{8650} + \cdots + \frac{45}{1708} = 0.26 \tag{4.13}$$

It can be seen that the damage that the battery has undergone in one year equals to 26%. The battery reached EOL when this damage becomes 100%. Thus it represents almost ¼ of the overall damage that the battery can undergo until reaching EOL.

4.3.3.2. Detailed explanation of the overall methodology

While the battery starts cycling, using power management of Architecture 1, as discussed in Chapter 3, the consecutive current zero crossings are found. The overall DOD profile between these two consecutive ZCs includes active as well as inactive periods. In order for the inactive periods to be eliminated and not take part at the cycling degradation of the battery, their value is being zeroed and not accounted later at the PM rule.

This DOD profile including only the active cycling time periods of the battery is being fed into the rainflow counting algorithm. The bins at the rainflow algorithm were set to be 1000 for higher accuracy. While this algorithm computes the number of cycles that the battery has undergone under specific values of DOD, the lookup function for the cycle life including temperature and DOD effects is used to compute the overall cycling that the battery could undergo if it was operating constantly under the DOD values found from the rainflow. The temperature that is used at the lookup function equals to the average temperature extracted from the simulation for the time period between these consecutive zero current crossings (for the ZCs micro-cycle).

After that a cumulative Palmgren Miners' rule is applied using the cycling from the rainflow (not taking into account the first bin with the inactive zero stress values) as well as the cycling from the lookup function, it calculates the total damage that happens to the battery during the time period between the ZCs micro-cycle. The damage is calculated as a percentage of the total cycle life of the battery. As it was already said before, the EOL of the battery is set to when the battery capacity reaches 80% of its initial capacity. In addition the EOL of an element is defined when the cumulative damage has reached the unity. Combining these two statements the equation that was used for the calculation of the capacity fading in Wh that the battery has undergone between these consecutive zero current crossings is the following:

$$cf_{ZCs} = 0.2 \times D(ZCs) \times Q_{updated} \quad (4.14)$$

Where,

- $\boldsymbol{cf_{ZCs}}$: the capacity that consumed from the battery in [Wh] during a ZCs micro-cycle,
- $\boldsymbol{D(zcs)}$: the damage that the battery has undergone as a percentage,
- $\boldsymbol{Q_{updated}}$: real time maximum available battery capacity

The factor of 0.2 in the Equation 4.14, indicates that the battery reaches EOL at 80 % of its initial capacity. The Battery capacity that is used at the equation symbolizes the capacity that the battery has at the specific time (real time battery capacity) that has been cycled. The remaining battery capacity is calculated after subtracting the capacity fading that has been calculated from Miners' rule from the battery capacity that the battery had before the ZCs event.

After reducing the battery capacity by a percentage it is checked whether or not the battery has reached 80% of its maximum initial capacity, thus EOL. If this is not the case, the battery continues cycling having the updated, reduced battery capacity until the next current zero crossing occurs, and the same procedure is repeated until End-of-life. When the EOL is reached, the model gives as an output the lifetime of the battery technology used, in years. It is worth pointing out the after every decrease in the battery capacity the overall maximum and minimum charging and discharging capacity values of the battery are updated in order to match the new capacity requirements.

It is worth pointing out that this capacity fading method is very dynamic as the resolution of the events is not in years or months but in ZCs micro-cycles. The capacity fading is happening for every zero crossings micro-cycle that the battery undergoes, thus the aging phenomena are accounted in very small battery cycling intervals making the methodology very realistic and accurate.

Efficiencies

In order for the dynamic capacity fading code to be as accurate as possible, different efficiencies were used for different battery technologies. The efficiencies of the different technologies were kept constant throughout the simulation and their value was decided after comparing the efficiencies of the same technologies from different sources [65] [66] [67] [68] [69]. It has been found from the literature that Lithium ion batteries and more specifically LiFePO4 have the highest efficiency of all the battery technologies while NiCd batteries have the lowest efficiency of all the technologies used. Lead acid batteries do experience high efficiencies with flooded batteries having 5% lower efficiency than VRLA batteries. Table 11 shows the efficiencies used for the different battery technologies.

Table 11: Different efficiencies used for different battery technologies

Technology	Efficiency [-]
LiFePO4	0.93
Sealed lead acid	0.90
NiCd	0.78
Flooded lead acid	0.85

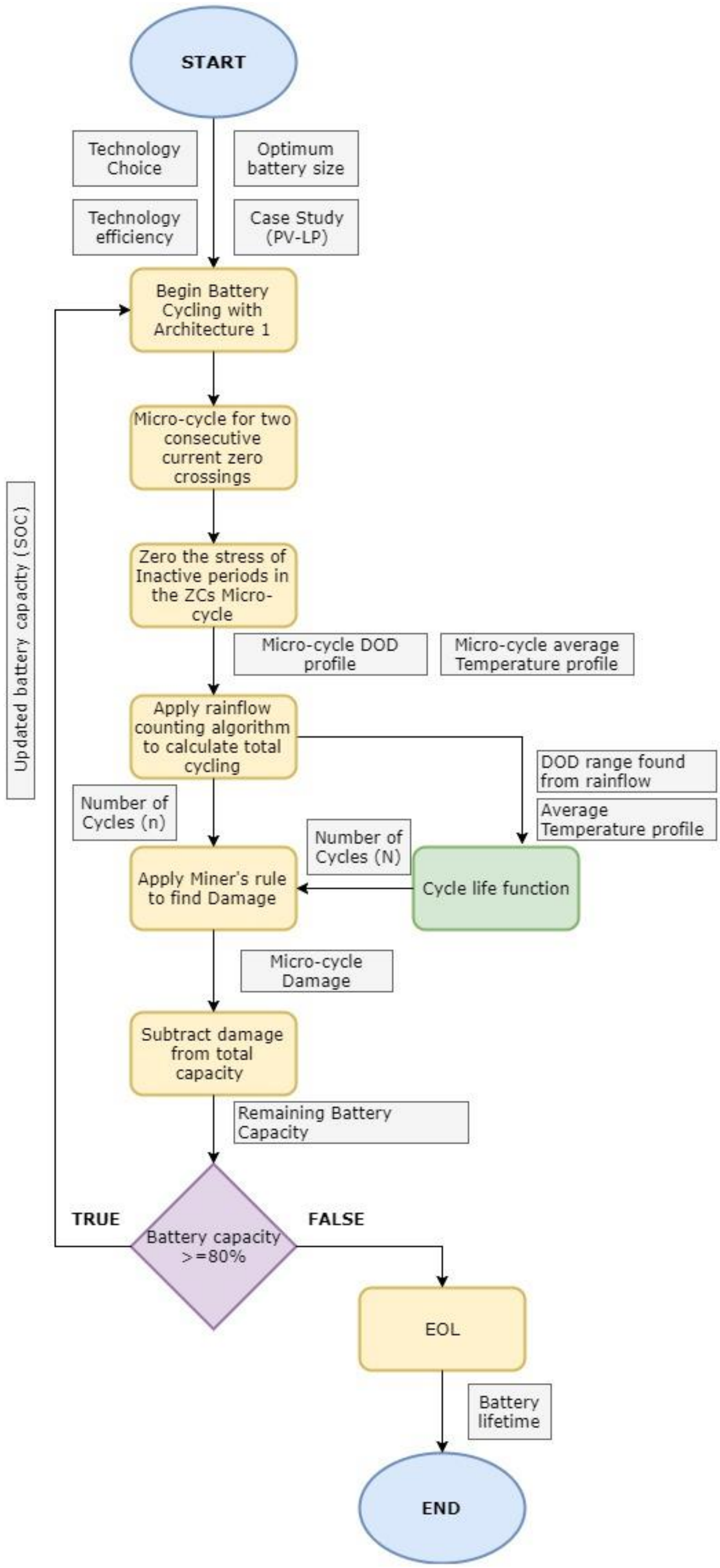


Figure 4-18: Block diagram of the steps followed for modelling dynamic capacity fading

4.3.3.3. Calendar aging

The concept for the calendar aging, as also described at the beginning of this chapter has to do with irreversible battery damage that occurs in times when the battery is resting, thus being inactive and not undergoing cycling. The main cause of the calendar aging is the temperature and not the SOC/DOD of the battery [70]. Most of the studies do not take into account the battery SOC when they measure calendar aging but mostly temperature, thus this is what it was followed for the approach in this study too [71].

In order to perform calendar fading the inactive periods of the battery were isolated from the active and the temperature profile between these inactive periods was used. It is worth pointing out that due to lack of information for all the battery technologies calendar fading was performed only for research and observation purposes for Sealed lead-acid batteries and it is not used further in the model.

After the inactive periods were calculated, curves from the same battery datasheets that were used for sealed lead-acid batteries before, were found and fitted for different temperatures. A reconstruction of the linear curves of battery capacity fading due to calendar aging in respect to inactive time for different temperatures is shown in Figure 4-19.

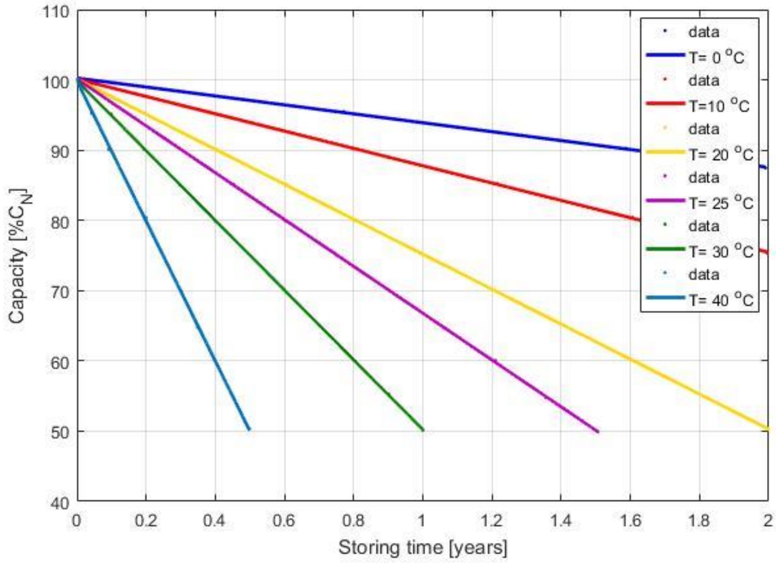


Figure 4-19: Reconstructed calendar aging curves for Sealed lead-acid [data sourced from [36]]

After fitting the curves into linear polynomials a relationship between them was found by considering the curve of 20 °C as a reference one and subtracting the slopes of the other curves from the reference. The relationship between the slope difference was not linear but it was fitted as a third degree polynomial and the curve is shown in Figure 4-20.

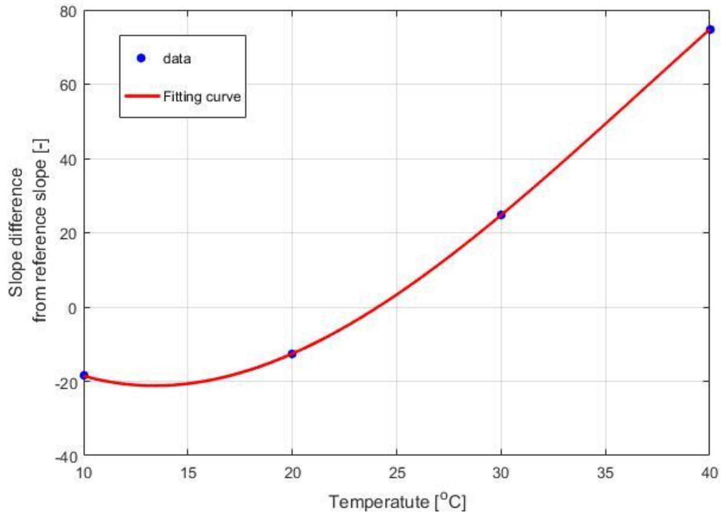


Figure 4-20: Slope difference fitting curve from the reference slope

The calendar fading was modemed as a linear function with slope depending on the temperature which is calculated form the third degree polynomial of the temperature difference. The equations used for calendar fading of sealed lead acid battery are:

$$calendar\ fading\ (\%\ Q_N) = slope(T_{avg}) \times inactive\ time\ period\ [years] + 100 \tag{4.15}$$

$$slope(T_{avg}) = slope(T_{ref}) - (b_1 \times T_{avg}^3 + b_2 \times T_{avg}^2 + b_3 \times T_{avg} + b_4) \times abs(slope(T_{ref})) \tag{4.16}$$

Where,

- p_1, p_2: linear fitting coefficients of the fitting curves,
- T_{avg}: average temperature of inactive intervals,
- T_{ref}: reference temperature,
- $b_1 to\ b_4$: fitting coefficients of the slope difference curves,
- C_N: rated battery capacity

The values of the coefficients of Equation 4.16 are shown in Table 12.

Table 12: Fitting coefficients of the slope equation

Coefficients	Value
b_1	-0.003109
b_2	0.3433
b_3	-7.525
b_4	25.5

In order for the calendar fading to be applied as accurately as possible to the inactive periods of the battery, rainflow counting algorithm and Palmgren Miner's rule were again used. The stress factor that was used as input in the rainflow algorithm now is the Temperature between these inactive time periods. More specifically as soon as one inactive period is identified the temperature profile in respect to minutes are fed into the rainflow algorithm, which is able to group and measure the total time that the battery was resting for a corresponding temperature stress. These time periods are used later in the Palmgren Miner's rule as the nominator. The denominator needs to represent the time the battery can last in specific temperature stress until the EOL is reached. In order to be able to calculate this time the terms of Equation 4.16 were rearranged setting the calendar fading term equal to 80% (EOL). The equation is used as follows:

$$inactive\ time\ period\ [years] = \frac{80 - 100}{slope(T_{avg})} \tag{4.17}$$

These time periods found for all the different temperatures extracted from the rainflow algorithm are used as the denominator in the Palmgren Miner's rule. The results in the lifetime of the battery after applying this method are highly pessimistic as the battery is able to last less than a year.

This is very logical as battery relaxation phenomena haven't been considered but instead every inactive period between the active charging discharging times of the battery was used for the calendar fading. Relaxation time or period is a non-linear chemical reaction that takes place inside the battery and it represents the time that the battery needs in order to reach equilibrium, so as the terminal voltage relaxes to the new steady state value, after a charging or discharging cycle [72]. It is evident that relaxing a cell after it has experienced discharge has an important advantage in its performance [73] [74]. Thus, when calendar fading is performed in every inactive period-when the relaxation time also takes place decreases drastically the lifetime of the battery, something that is not realistic. It is worth pointing out that most of the models that consider calendar fading of the battery experience very large periods of battery inactivity, mainly because it is used on battery storage, thus it is much easier to account for the relaxation time of the battery too.

To conclude, calendar fading is not considered in the construction of the dynamic capacity fading model that is proposed in this study mainly due to lack of data for all the battery technologies as well as due to the difficulty of considering the relaxation period in the model which is also beyond the scope of this thesis.

4.4. Results of Dynamic lifetime estimation model

- ***Validation of Dynamic capacity fading model***

In order to be able to validate the model constructed for the dynamic capacity fading of the battery, it was compared with the same model that Zero crossings lifetime estimation method was compared. The difference is that the empirical model was applied dynamically into the model used for this project having a lithium iron phosphate battery undergoing the cycling from Case study 2 and temperature effects were not excluded this time. The results for the lifetime of LiFePO4 battery lifetime in years from the two models are shown in Table 13.

Table 13: Results and comparison between the empirical model and our model

Lifetime [years]	**Dynamic Empirical Model**	**Dynamic Capacity Fading**	**Deviation From Empirical Model**
	17	8.62	49%

In general the empirical model states that it is too optimistic in operating temperatures between 0-25 ^{O}C [63]. The average operating temperature from the temperature profile that was used in this report equals to 28 ^{O}C. However the average temperature that is taken into account when applying the empirical model dynamically is the average temperature between the zero crossings found, thus the temperature between the ZCs micro-cycles. Thus, there are many times that the average temperature used is between 0-25 ^{O}C, leading to an optimistic lifetime prediction for the battery lifetime. More specifically the mean temperature calculated and take into account for all the zero crossings found in one year is shown in Figure 4-21.

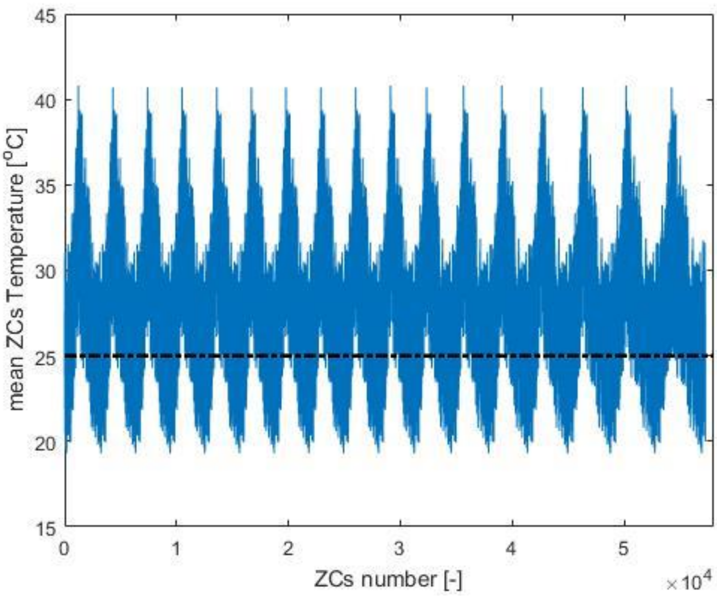


Figure 4-21: All the average temperature values accounted between the ZCs micro-cycles occurred for one year

While most of the average temperatures used for the dynamic capacity fading are above 25 ^{o}C there is a considerable amount of zero crossings micro-cycles where the temperature is below 25 ^{o}C, thus below the dashed line in Figure 4-21. More specifically 1/3 of all the zero crossing temperatures is below 25 ^{o}C, thus it is safe to say that the lifetime number calculated from the empirical model is very optimistic while the number calculated using the dynamic capacity fading method is more realistic and even a little bit pessimistic.

It is worth pointing out that the first time the empirical model was used for the validation of the Zero crossings lifetime estimation method the temperature effects were not considered and the deviation between the modelling and the experimental results was smaller. For the validation of the dynamic capacity fading though, the temperature effects are included in both models, experimental and non-empirical, thus the difference between them becomes bigger as the first one is very optimistic.

- ***Lifetime Results***

After applying dynamic capacity fading at the way it was explained above for all the battery technologies and both case studies, the results are shown in Table 14.

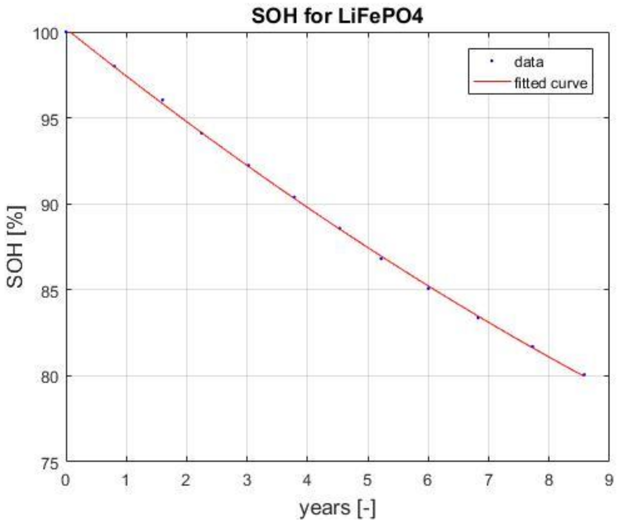
Table 14: Lifetime results from dynamic capacity fading for four technologies

Battery Technology	**Lifetime [years]**	
	Case Study 1	**Case Study 2**
LiFePO4	6.92	8.62
Sealed lead-acid	1.94	2.68
NiCd	0.77	1.02
Flooded lead-acid	1.67	2.26

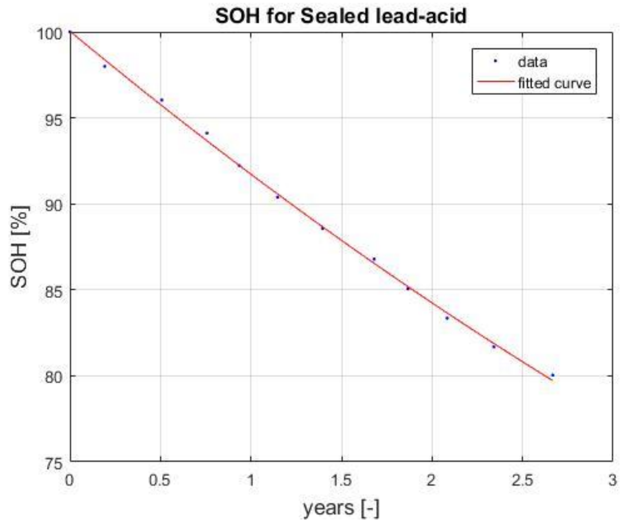
Comparing the lifetime results of the batteries it is clear that Lithium ion battery is the one that has the highest lifetime in both case studies filled by sealed lead acid and flooded lead acid respectively. Lastly, the NiCd battery chosen for this study represents the technology with the lowest lifetime reaching almost one year before needing a replacement.

- ***State of Health Results***

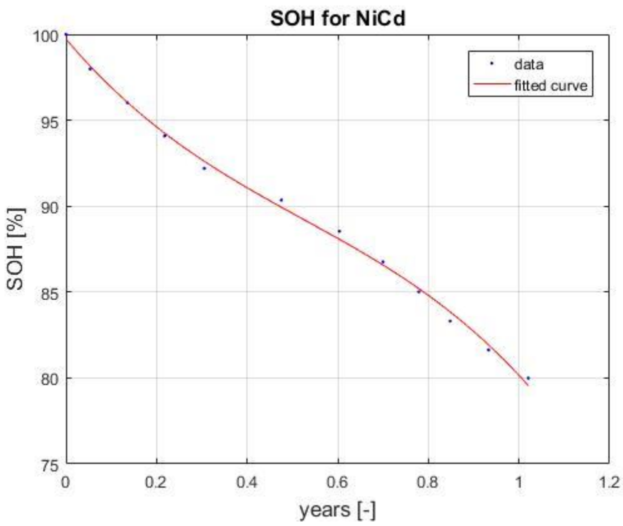
It is very interesting to see the rate at which the battery capacity degrades for every one of the battery technologies. For this purpose the state of health of the battery was calculated as a percentage of the rated battery capacity while the battery was still at operating conditions, meaning having a capacity above 80% of the rated battery capacity. The SOH of the batteries versus the number of years that represent their lifetime is illustrated in Figure 4-22 for all the technologies separately.



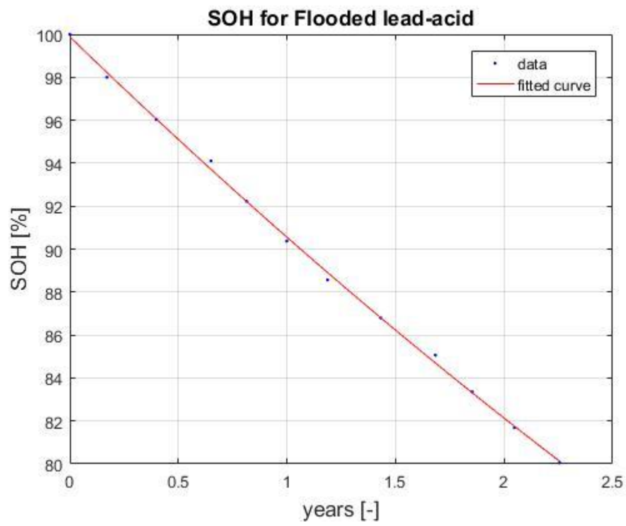
(a)



(b)



(c)



(d)

Figure 4-22: State of Health in respect to time in years for (a) LiFePo4, (b) Sealed lead-acid, (c) NiCd, (d) Flooded lead-acid batteries.

In order to be able to compare the aging rate of the battery the SOH data with their fitting curves were illustrated in a single figure, Figure 4-23.

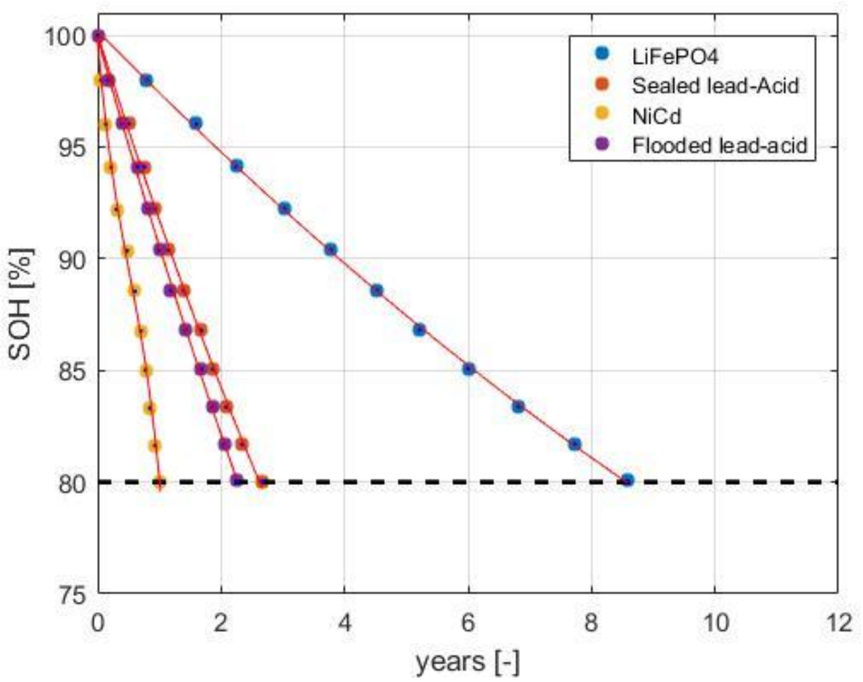


Figure 4-23: SOH of four battery technologies, Case study 2

It can be seen that while Lithium ion battery is degrading gradually over its 8 years of lifetime almost linearly, the other technologies are aging much more drastically having smaller lifetime. The aging rate of NiCd battery in the specific application of Solar Home Systems is appear to be very high and not gradual as it almost drops to 80 in the first year of usage. The capacity fading rate of the lead-acid batteries is more gradual but still steep as the battery presents almost 1/3 of its capacity fading every year.

4.5. Conclusions

- The main conclusions that can be drawn from this chapter, in terms of the dynamic lifetime estimation methodology is that it can be considered accurate enough and a little bit of pessimistic taking into account the comparison of the method with empirical model. More specifically, the fact that the model takes into account active and inactive periods of the battery as well as temperature and DOD factors makes it very suitable for any kind of low power application.

- In terms of battery technology comparison it is clear that lithium ion and more specifically LiFePO4 battery experiences higher lifetime in all load profiles used. Thus, even though it undergoes different cycling it is still able to maintain higher lifetime. Lead acid batteries on the other hand, have lower lifetime than lithium ion battery and NiCd battery exhibits the lowest lifetime in both load profiles. It is worth pointing out that the results shown are for specific battery technology brands from different manufacturers as their datasheet lifetime curves were used. It is very much expected that the lifetime results of the batteries to change in case that other datasheet or technology curves are used. This is one of the main advantages of this dynamic capacity fading model. It can be adopted in any battery as long as the temperature lifetime curves in respect to DOD are provided or easy to be constructed taking into account experiments.

- Another conclusion that can be drawn is that in the specific load cases of Solar Home Systems the average temperature is very close to the ideal operating temperature of the all the battery technologies, thus it does not affect the lifetime results that much. It is very important to state that the linearity of the temperature as accounted for the construction of the cycle life equation is valid for temperatures between the range of temperature curves provided by the manufacturer, thus between 20 to 45 ^{O}C. For operating temperatures outside this range, the equation will be able to provide a result but it is probably going to be far from realistic as the temperature linearity might not be followed in those temperatures. As it was also discussed in detail in Chapter 2 in extreme temperatures the batteries undergo accelerating aging with different rate depending on the technology. To sum up, it is very possible that the equation of the cycle life that includes temperature linearity (Equation 4.5) will give far from realistic and accurate results in extreme temperatures. On the other hand, this method can be applied in a very wide range of applications as most of the developing countries and regions and not only, lie in latitudes with temperatures between the range of 20 to 45 ^{O}C.

Evaluation of dynamic capacity fading model

When evaluating the capacity fading/lifetime estimation model we have to make sure that the main challenges these kind of models face were overcome and that the main criteria that these models need to satisfy have indeed been satisfied. In order to do that the five points in section 4.2.3 were argued in respect to the model of this study.

1) The operating conditions of the specific application of Solar Home Systems were indeed considered during the construction of the lifetime estimation method and the stress factors taking place in such applications were used in the determination of the aging processes. In such systems the main stress factors that are taking place is the DOD fluctuation due to battery cycling and temperature effects. These two stress factors were combined together and used for the dynamic capacity fading. In addition, considering that there is no fast charging and discharging in such applications the C-rate effect was excluded for the aging process.

2) The EOL of all the battery technologies used was indeed predetermined as the cycle life datasheet curves that were used for different temperatures and the equations constructed for the cycle life take into account EOL conditions for specific temperatures and DODs into a single cycle life function.

3) As the data for the lifetime of the battery were extracted from battery datasheets the lifetime estimation is performed in battery and not in cell level for the application of the Solar Home Systems

4) The following questions were able to be answered:

How long will a specific battery brand, (from a specific manufacturer) last when different applications and operating conditions are applied to it?

The lifetime estimation method's inputs are based on battery manufacturer lifetime dataset curves. Thus, it can be applied to any manufacturer and any battery technology or brand as long the specific lifetime curves are given by the manufacturer. In addition, given different load profiles as input to the model all kinds of low power applications could be applied and have results in this lifetime estimation model.

How long will a new and more advanced with different material composition battery design last in a specific application?

This question can be again answered by arguing that the manufacturer of this new kind of battery is able to provide the cycle life curves for the different temperatures. If this is the case then this lifetime estimation method can be applied in any battery type.

5) As most of the lifetime estimation models, the main and real challenge that this model had to overcome was the limited amount of data provided by manufacturers for renewable applications. For the case of the battery technologies used in this study, some of the lifetime curves that were used for the batteries had to be constructed and not taken directly from the datasheets. Thus, this challenge was not overcome

completely. It is worth pointing out, that in case that those curves were provided directly by manufacturers the final result could be more accurate. But in terms of methodology and modelling the dynamic capacity lifetime estimation method that was used in this report can be considered very accurate.

The aforementioned point is also the main reason that calendar fading couldn’t be performed as curves or models for calendar fading couldn’t be found for all the battery technologies that are examined here, in order to be able to make a meaningful comparison.

Chapter 5

Hybrid Battery

In this chapter the methodology for the Hybrid battery storage is explained. In order to be able to use a hybrid battery storage option two power management algorithms are constructed and used for the battery cycling in the dynamic lifetime estimation model. The two batteries forming the hybrid battery are cycled differently in each one of the power managements. The dynamic lifetime estimation model is applied at both batteries simultaneously for both power managements for a System lifetime of 25 years.

5.1. Introduction

One of the most burning technical issues concerning Solar Home Systems is the high battery upfront cost as well as the battery reliability. The sizeable proportion of the upfront battery cost in a SHS combined with the limited lifetime of the battery compared to the other elements forming a SHS makes the issue even more significant. Considering the battery as the most expensive component in a Solar Home System, the idea of Hybrid Battery is going to be examined. This chapter explains the methodology followed for the hybrid battery configuration.

Hybrid Battery (HB)

The Hybrid battery is defined as the combination of two battery technologies possessing different sizing percentage of the overall battery size that a system needs. These two batteries are used together in the system and their cycling is a result of the power management used.

Hybrid Battery (HB) ratio

Hybrid battery ratio is defined as the percentage of the overall battery size possessed by the secondary battery technology to the percentage of the overall battery size possessed by the main battery technology. The overall battery size is the optimum battery size needed for every set of PV-load profile as calculated in Chapter 3. More specifically, the hybrid battery ratio is expressed as shown in Equation 5.1. Main and secondary battery technologies are defined differently for the two different power managements and are explained later.

$$HB\ ratio = \frac{\%Size_{secondary}}{\%Size_{main}} \tag{5.1}$$

Main battery technology

In this study, in both power managements that will be introduced in the following sections, the term "main battery" is used to represent the battery technology that has the primary role in the power managements having priority in charging and discharging.

Secondary battery technology

The term "secondary battery" in the two power managements represents the battery technology that is used as complementary in the main battery technology, handling specific load cases differently for different power managements.

5.2. Methodology

Two different methodologies for the Power Management in the Solar Home System, using Hybrid battery Storage were used. The first one uses a main battery handling most of the load and a secondary one in times that the first is not enough. The second power management uses a certain C-rate threshold. The loads above that threshold (mainly the peaks in the load) are handled by one of the batteries, while the loads below that value are handled by the other one (average load). These two power managements were used instead of Architecture 1 in the dynamic capacity lifetime estimation model, in order to determine the power flow in the system.

5.2.1. Power Management A (PM A)

Main battery technology: For this power management method, one of the batteries is used as the main battery, handling most of the load. This battery has a priority in charging when there is an excess of energy as well as in discharging, when there is a deficit of energy. It has the primary role between the two batteries consisting of the hybrid system

Secondary battery technology: In times when the main battery is fully charged or is unable to handle full or a part of the load, then the secondary battery kicks in complementing the contribution of the main battery. The main role of this battery is to support the main battery whenever it is needed depending on the load profiles use each time

This power management flow chart is summarized through an illustration shown in
Figure 5-1. Every time there is a deficit or surplus of energy the priority goes to the main battery checking whether it has enough space to be charged or enough energy to give to the load and be discharged. If this is not the case then the secondary battery is checked and charged with full or remaining surplus and discharged by the remaining unsatisfied load that the main battery couldn't handle. In times that both batteries are fully charged and there is still extra energy production not needed by the load, this energy is dumbed. On the other hand, there are some times that the system is not able to satisfy the load completely mainly when there is very high demand and low energy production, in the winter or during the evening. However this system downtime was set to be very low during the sizing of the battery carried in Chapter 3.

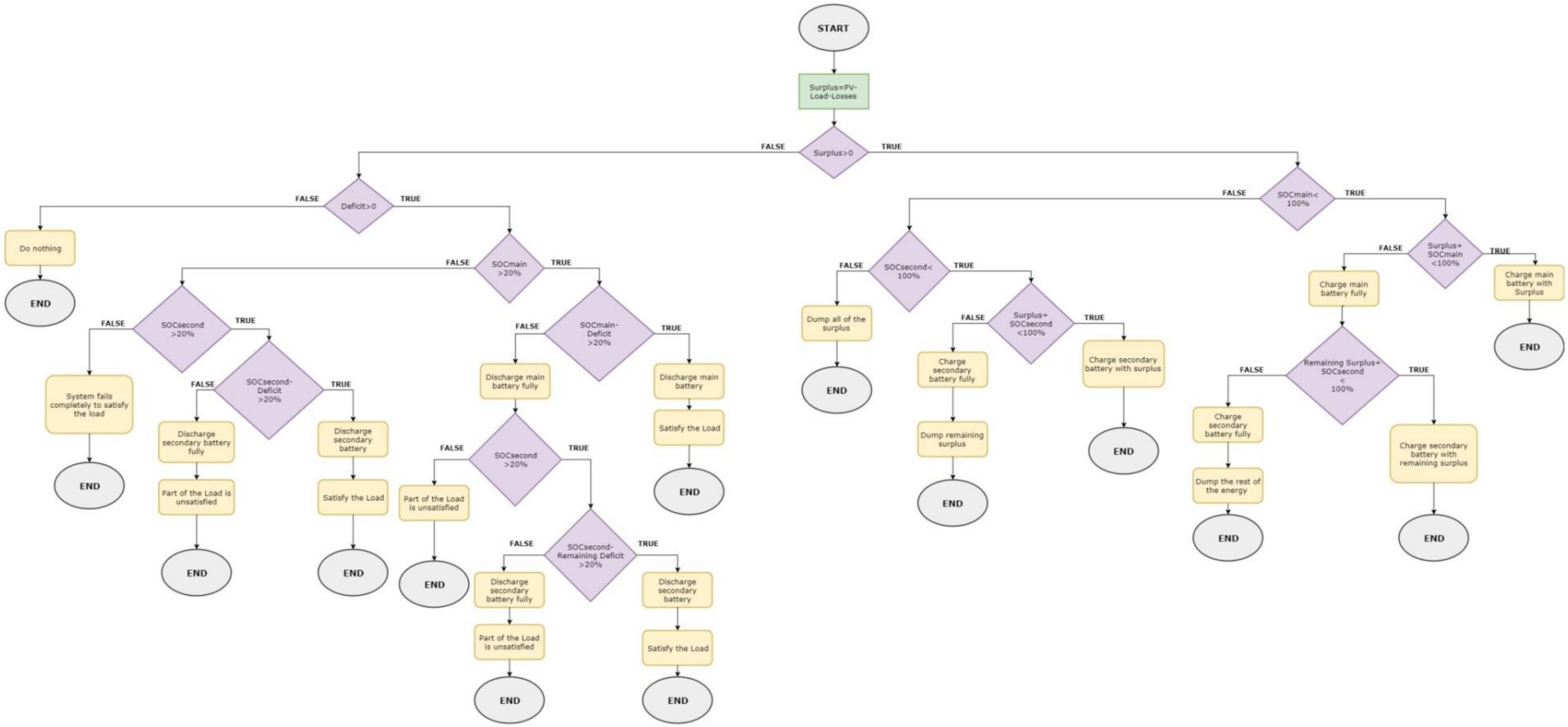


Figure 5-1: Energy balancing algorithm for Hybrid Battery System having a main and a secondary battery (PM A)

5.2.2. Power Management B (PM B)

For this power management method the main control that takes place is the C-rate value of the system for a specific minute. The main idea behind this method is that one of the batteries has to handle the power peaks of the system while the other one handles the average power values. Doing that, the batteries do not experience deep charge and discharge cycles, helping the extension of their lifetime. Furthermore, in times that the load is not satisfied and one of the batteries hasn't been empty yet, then this is the one that kicks in to handle the load. This power management flow chart is summarized through an illustration shown in Figure 5-4. In order for the C-rate threshold to be set, the C-rate using the overall battery size for each case study, was found from one year of simulations that were done beforehand. Figure 5-2 shows the C-rate as extracted from one year of simulations for Case Study 1 (low LP) and Figure 5-3 shows the yearly C-rate for Case Study 2 (medium LP).

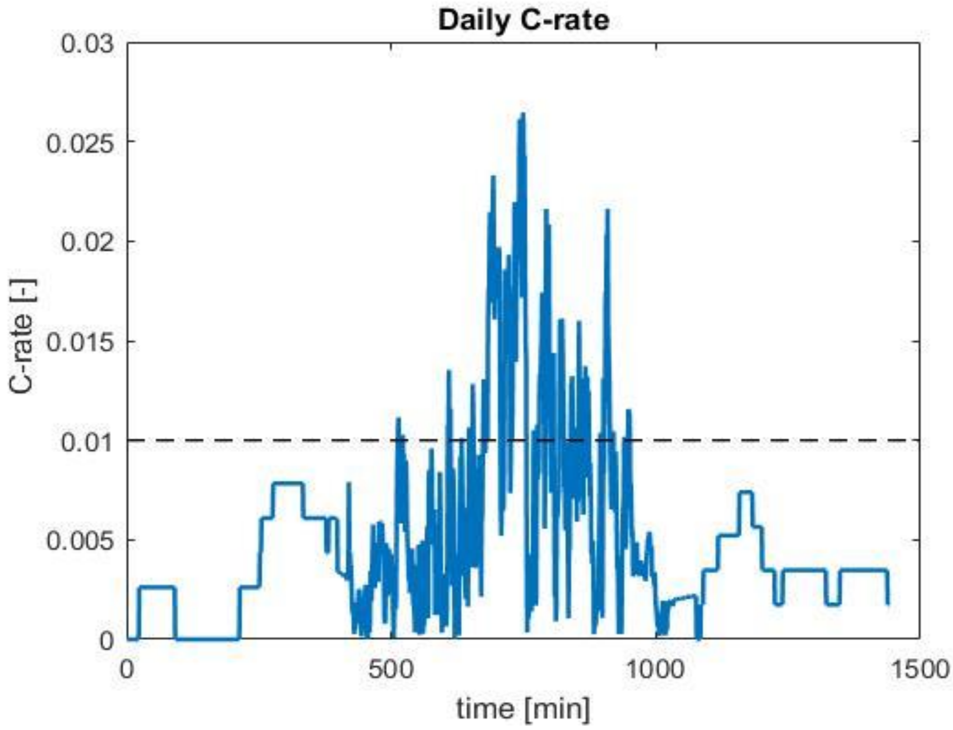


Figure 5-2: C-rate for one day as extracted from a yearly simulation for Case study 1 (low LP)

For Case Study 1 (low LP) the C-rate threshold was decided to be equal to 0.01, as the dashed black line in Figure 5-2 shows.

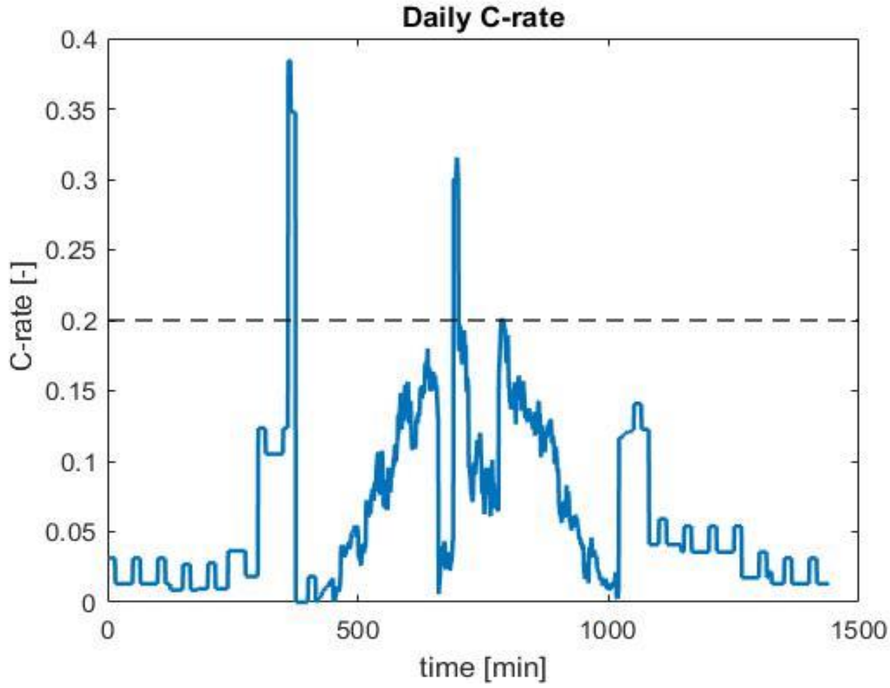


Figure 5-3: C-rate for one day as extracted from a yearly simulation for Case study 2 (medium LP)

For Case Study 1 (low LP) the C-rate threshold was decided to be equal to 0.2, as the dashed black line in Figure 5-3 shows.

Main battery technology: For this power management method the main battery will be defined as the one that handles the average power of the system. More specifically as it is seen from the C-rate graphs, there are some big power peaks. The main battery is responsible on handling everything up to a specific threshold point that is defined differently for different load profiles.

Secondary battery technology: The secondary battery will be defined as the one that handles the power peaks of the system. Whenever the C-rate is higher than the threshold value that was set, the secondary battery handles the remaining power above this threshold.

Due to the fact that one of the batteries is going to be working constantly handling the average power of system while the other one will only be working in times that there are peaks, the main battery needs to be bigger than the secondary one. Thus, the HB ratio combinations when the secondary battery is bigger than the main are not going to be tested as it doesn't make sense. This is also shown in Figure 6-8 where the blue shadow represents the cases where power management B was used.

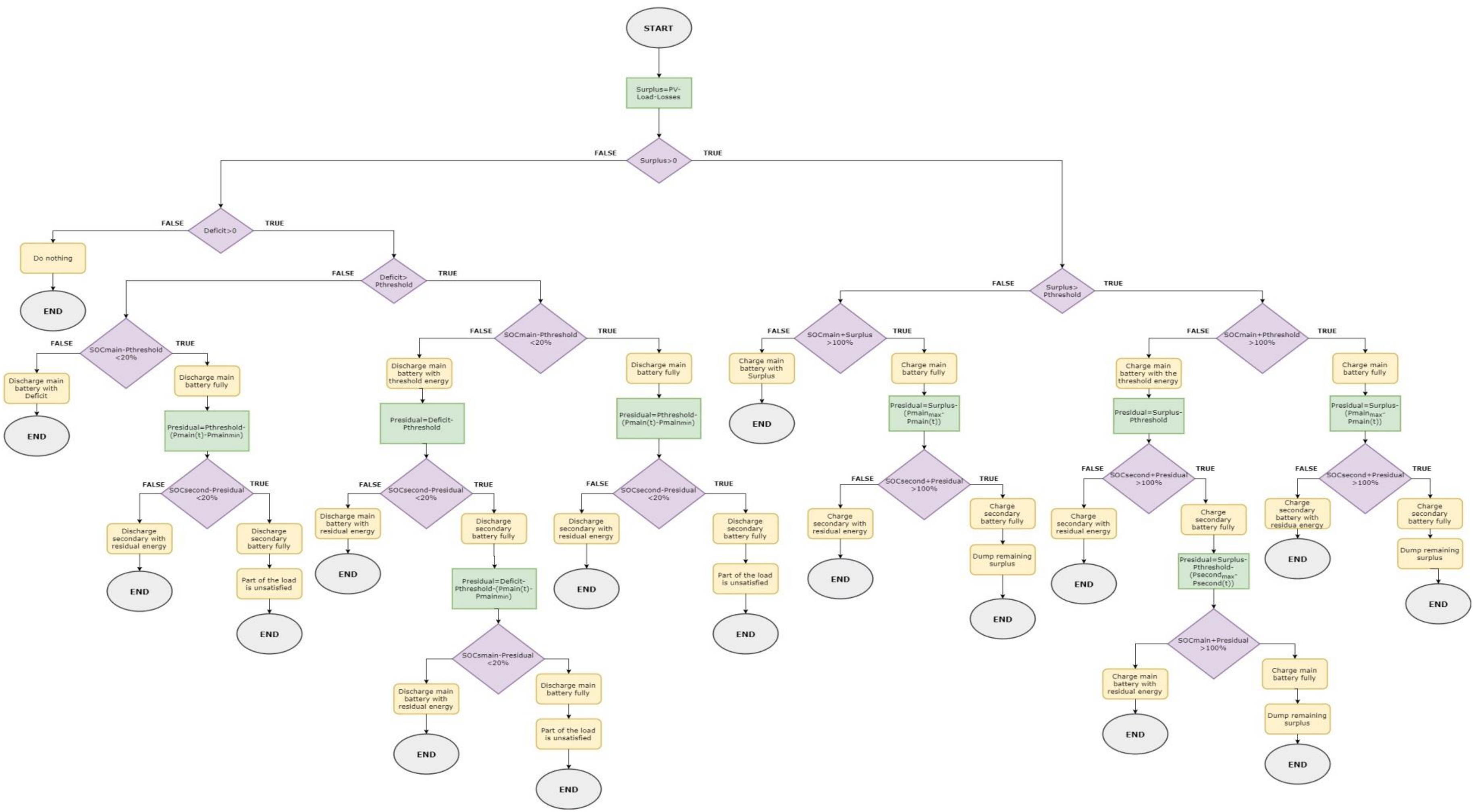


Figure 5-4: Energy balancing Algorithm for Hybrid Battery System based on C-rate threshold (PM B)

5.3. Lifetime Calculation for Hybrid Battery System

For the calculation of the lifetime of the two batteries forming the Hybrid Battery system, dynamic lifetime estimation model was applied for both batteries simultaneously. In a more detailed explanation, the first step of this algorithm is to choose which Case study and which two of the four different technologies that are examined in this report are going to be used forming the HB. After having already calculated from the simple battery sizing algorithm explained in Chapter 3, the optimum battery size for the specific case study, the percentage of the total size that each one of these two technologies is going to have needs to be determined. In order to check as many options as possible this HB ratio is going to be varied. The size of each battery in the HB system is a percentage of the optimum battery size determined in Chapter 3 for each one of the Case studies. Equations 5.1 and 5.2 show how the battery size for each one of the two batteries, is calculated:

$$Size_{technology_1} = r \times Size_{optimum} \tag{5.2}$$

$$Size_{technology_2} = (1 - r) \times Size_{optimum} \tag{5.3}$$

Where,

- $\boldsymbol{Size_{technology_1}}$: the size of one of the batteries consisting the Hybrid battery system,
- $\boldsymbol{Size_{technology_2}}$: the size of the other of the batteries consisting the Hybrid battery system,
- $\boldsymbol{r}$**:** the percentage of the optimum battery size varied between 10-90 % ,
- $\boldsymbol{Size_{optimum}}$: the optimum overall battery size (370 Wh for Case study 1, 1150 Wh for Case study 2)

As it can be seen from Equations 5.2 and 5.3, the two different battery sizes are complementary to each other, and if added up they are equal to the total storage size that the system needs.

The next step is to apply the different efficiencies corresponding to the battery technologies that are used. Starting the simulation for one Case study, the chosen power management is applied and the batteries start cycling. The data resolution is minutely for one year, thus a check for consecutive zero current crossings, happens for both batteries every minute. If two consecutive zero current crossings are found for one or for both of the batteries, then the DOD of the specific battery and temperature profile between this time interval is fed to the rainflow counting algorithm.

As the rainflow algorithm finds the exact number of cycles that the battery has undergone for specific DOD values for this ZCs micro-cycle time interval, the cycle life lookup function that was constructed using the datasheets for the specific battery technology examined, is used. This function, calculates the total cycling that the battery can undergo under the rainflow-extracted DOD values and the temperature profile that is given. Having these, Palmgren Miners' rule is applied for each one of these stress levels identified between this time period, and a cumulative damage percentage is calculated.

This damage is used to calculate the total capacity fading that the battery has undergone during this period, and subtracted from the initial battery capacity. A check is made, whether or not the battery has reached EOL. If this is true, then the battery examined is replaced with a fresh one, having the initial proportional battery capacity that was defined at the beginning, otherwise it continues cycling with reduced capacity, undergoing even more fading until the EOL is reached. This procedure is illustrated in detail in the block diagram of Figure 5-5.

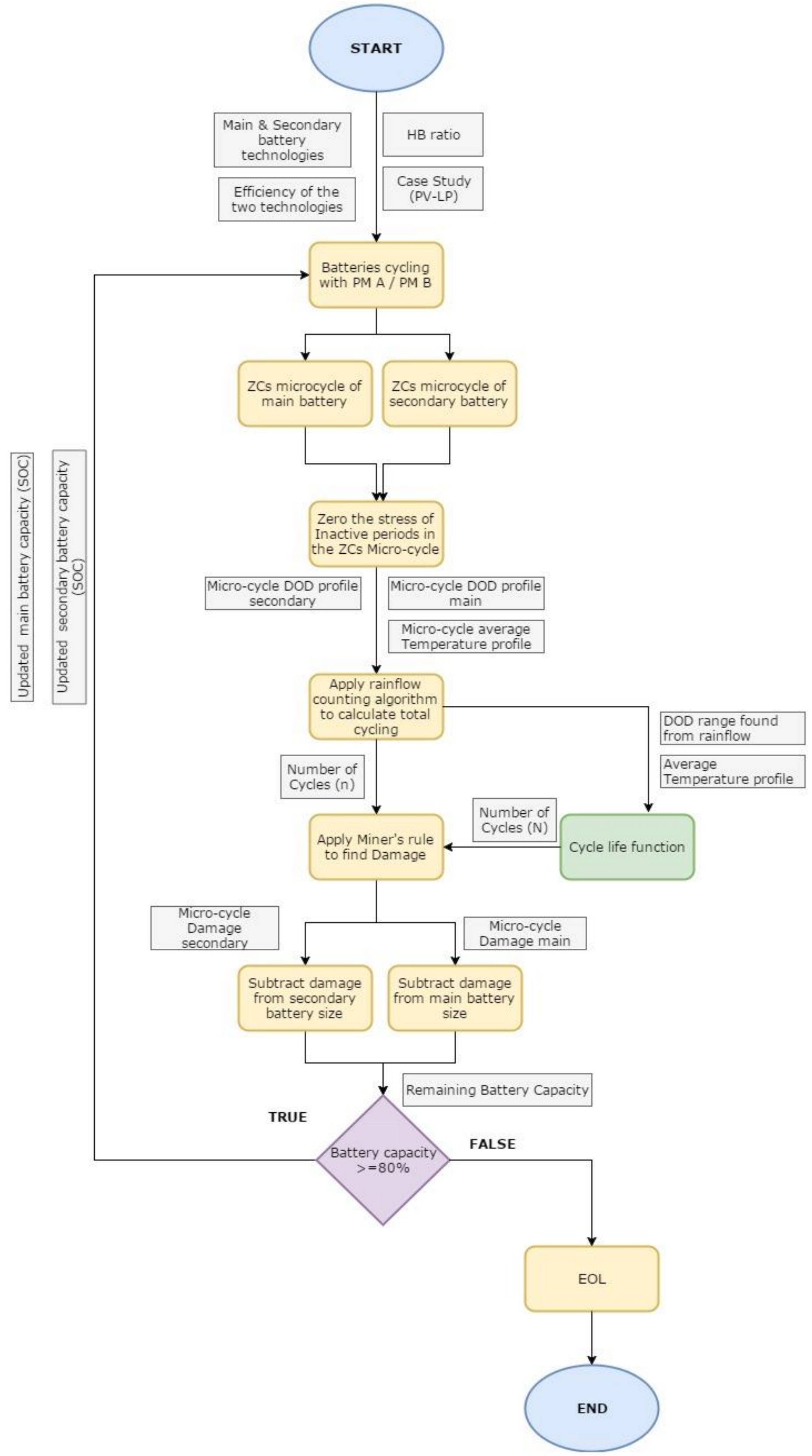


Figure 5-5: Block diagram of application dynamic lifetime estimation method to the HB storage system

The different battery technology combinations that are constructed and examined for the hybrid battery configuration are summarized in Figure 5-6. These combinations were between two battery technologies each time, with one of them representing the main battery technology and the other one the secondary. The diagonal cells of the figure represent the single battery storage options. All of the storage configurations hybrid and not that are shown in this are going to be examined and compared after applying the cost functions introduced in Chapter 6.

Secondary / Main	LiFePO4	Sealed lead-acid	NiCd	Flooded lead-acid
LiFePO4	**100 %**	HB ratios	HB ratios	HB ratios
Sealed lead-acid	HB ratios	**100 %**	HB ratios	HB ratios
NiCd	HB ratios	HB ratios	**100 %**	HB ratios
Flooded lead-acid	HB ratios	HB ratios	HB ratios	**100 %**

LiFePO4 **main**

Sealed lead-acid **main**

NiCd **main**

Flooded lead-acid **main**

Single technology

Figure 5-6: Different battery technology combinations to be examined

Chapter 6

Cost Function

The main goal of this chapter is to examine whether or not a hybrid battery option would be more ideal than just using a single battery technology, for the application of the SHSs and the specific load profiles that are examined in this study. In order to have a meaningful comparison, a cost function representing the comparison reference between the different storage choices available for the application of SHSs will be constructed and applied.

The different parameters that were used for the construction of this function and a detailed explanation of its construction step by step are given. For the purpose of this study two cost functions are constructed. One function was constructed for the individual battery technology choice and one for the hybrid battery (HB) storage option.

The individual battery cost function in combination with the dynamic capacity fading/ lifetime prediction method that was introduced in Chapter 4 were applied for a System lifetime of 25 years for all four battery technologies of interest and the two case studies. The results are presented and analysed at the end of this chapter along with a sensitivity analysis that was carried out for different battery costs.

The hybrid battery cost function in combination with the dynamic capacity fading ,lifetime prediction method that was introduced in Chapter 4 were applied for a System lifetime of 25 years for all HB technology and sizing combinations and the two case studies. The results are presented at the end of this chapter.

6.1. Introduction

The battery technology selection for a specific application can be a non-trivial issue due to the fact that many technical and economical parameters need to be taken into account for this decision. In most studies the comparison of different storage options is made having in mind a number of key technical features of the batteries. While some of the considerations have to do with the performance and life of the battery, others have to do with parameters such as DOD, efficiency, temperature sensitivity calendar and cycle life. The type of the application as well as the location that this application is going to be implemented along with the corresponding ambient conditions that come with the location, are very important to be considered too. Last but not least, the economic factors that relate the application and the battery costs are very important [28]. Battery lifetime, with all the parameters that affect it (ambient conditions, specific application cycling, DOD, C-rate, etc.) is a very important aspect that needs to be accounted along with the different battery costs because it increases the running costs of an application. During the lifetime of a Solar Home System the battery will need many replacements depending on the technology that is used. Thus, it is very important for the selection of the battery to account the future battery costs in the time of the replacements.

As these parameters and categories might overlap in many cases, the technology storage comparison is a very difficult procedure. The discretization between these parameters as well as their selection and the way they are going to be combined for the battery comparison is the main challenge of the comparison procedure

Having all of the above in mind, this chapter introduces an overall cost function that takes into account as many battery parameters as possible, combining the lifetime of the battery with its present and future costs. This cost function is going to be used as a comparison measure between the different battery technologies as well as the different hybrid configurations helping to reach to the best storage solution for each load scenario.

6.2. Theoretical approach

The importance and connection of different parameters that need to be considered for the cost function

The main goal of the cost function is to combine as many battery characteristics and sensitivities together as well as battery lifetime with battery cost while taking into account future battery trends into a single function. The parameters that were used, their connection as well as the way they are depended from one another are shown in Figure 6-1 . In this figure, the dashed lines show the interdependencies between the different parameters, while the arrows show all the parameters considered for the construction of the cost function.

To begin with, the location at which the system is going to be implemented is very important because the ambient conditions are different for different locations. The most important ambient condition that is taken into account for the cost function is the temperature and how the battery lifetime is affected by the ambient temperature. Secondly, the type of the application for example SHS in combination with ambient conditions for example sunshine, determines the cycling that the battery is going to undergo during its operation. Moving forward, depending on the battery technology that used, the efficiency is going has to be different, as well as its sensitivity to the DOD levels, at which the battery operates and its temperature sensitivity. The DOD levels are determined from the battery cycling and as said before from the ambient temperature. Having all these as inputs the capacity fading rate (taking into account aging mechanisms that take place into the battery through its operation depending on the chosen technology) of the specific battery technology can be determined and the lifetime of the battery can be calculated.

In addition, after being able to calculate the lifetime of the battery the number of battery replacements that are needed throughout the system lifetime can also be computed. Lastly, the current battery costs, depending on the technology are taken into account for the first time that the battery was used, and the future battery cost trends are taken into account for the times that the battery replacements need to be done. The overall cost function has to be conducted by considering all of the above.

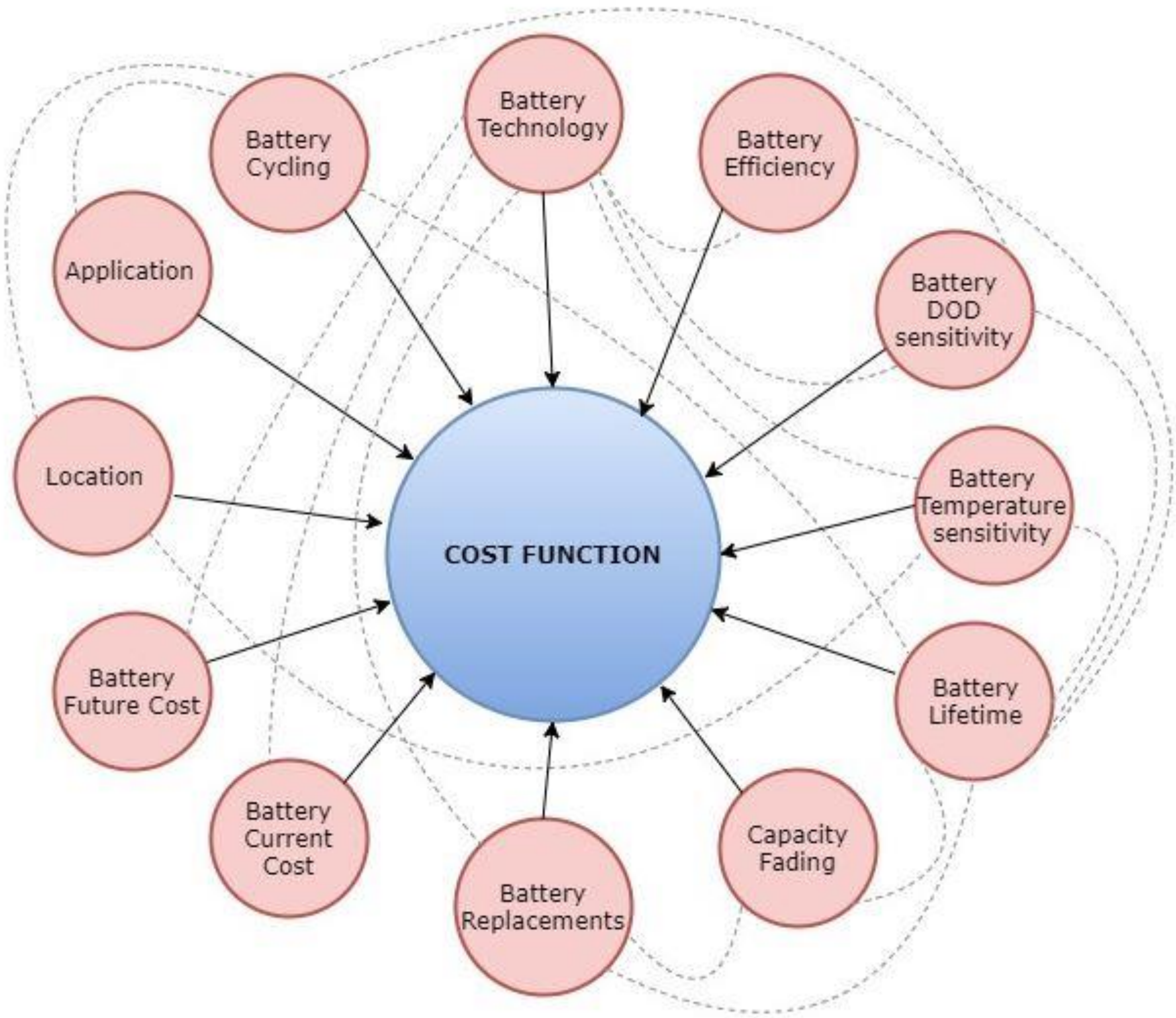


Figure 6-1: Parameters taken into account for the cost function and their interdependencies

6.3. Future Battery Cost Trends- depending on the battery technology

It is evident that the energy storage has already started becoming a huge player concerning the global energy market. It is also fact that it will continue to grow even more for the foreseeable future. This has as a result for the battery component cost to start declining enhancing even more the benefits of the battery storage, making energy storage combined with renewable energy generation, an attractive solution to the upcoming fossil fuel depletion and climate change. This price reduction for many battery technologies has already become evident while Bloomberg New Energy Finance predicts that the price for battery technologies will drop to $ 120/ kWh by 2030 [75].

The decreasing battery cost trends, refer mostly to lithium ion batteries that have shown the more drastic price reduction in recent years, especially in electric vehicle applications while other technologies such as advanced lead-acid, flow batteries, etc. have shown a downward trend cost but in a less pronounced manner. However, while the technology is advancing, the battery technologies will continue experiencing cost reduction due to performance improvements that will lead to higher deployment [28].

In 2015, lithium ion battery technology accounted for 95% of the new-energy storage deployments. This is an evidence of the increasing interest that is shown in lithium ion technologies. This technology is widely used in renewable, automotive applications consumer electronics and electric vehicles as their safety and performance have been increasingly improved. Lithium ion batteries can work in applications that require high power density providing high amount of energy for a short time period as well as in applications that require high energy density providing lower amounts of energy for longer time periods. To sum up, lithium ion batteries have become a broadly used technology in applications for stationary energy storage across the grid, industrial and residential systems as well as large utility-scale installations for energy transmission and distribution [76]. Bloomberg Energy Finance in a survey shows the continuing decrease in Lithium ion battery for automotive applications from 2010 to 2016 stating that technology improvements and the competition between the different Li-ion manufacturers have led to these trends, as also shown in Figure 6-2.

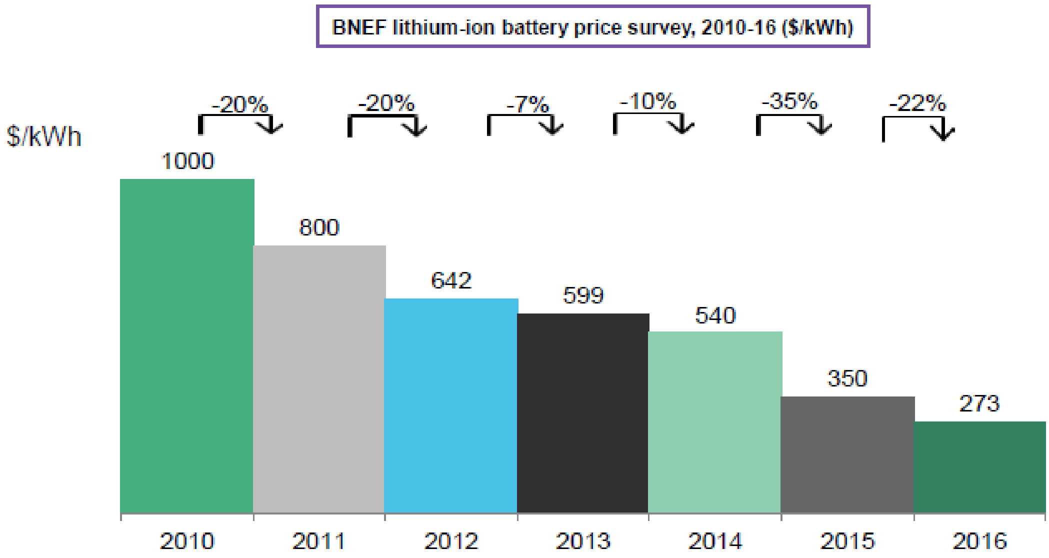


Figure 6-2: Reduction of cell plus pack Li-on prices. The cost presented is the average cost between the surveys taken place for the specific years [as shown in [77]]

It is worth pointing out that, while Li-ion prices for EV applications seem to be decreasing drastically reaching very low price levels, for residential applications using renewable energy sources Li-ion technology is still considered as the most expensive between all the technologies even though it again has a downward trend in the past years. It is also foreseen that this trend will continue but not in such a steep manner as it happens for EV applications [78]. However the increasing use of li-ion batteries in the EV applications is the one that also determines the general decreasing cost that this technology exhibits.

However, characteristics such as capability of long term storage as well as high power performance of lead-acid batteries, in combination with their already very low prices, allow them to remain a competitive storage solution in the energy market [28]. Lastly, Nickel Cadmium batteries can be considered as an inexpensive solution for low power applications such as Solar Home Systems [79].

6.4. Cost Function Construction

Taking everything that has been discussed into consideration the construction of the cost function considers as many battery parameters as possible combining upfront and lifetime costs as well as future battery trends. Figure 6-1 shows all the parameters that used for the construction of the battery cost function while Figure 6-3 groups the main considerations into two factors showing them in a simplistic way. From the latter figure it can be seen that the cost function consists of two main parameters: Upfront battery cost and lifetime-running cost.

Upfront cost represents the cost of the battery the first time that is going to be installed considering prices for the year when the total system was implemented. Upfront cost is directly proportional to the battery size and differs between different technologies. Lifetime cost on the other hand, is the total cost calculated from the number of the battery replacements that are needed throughout the system lifetime. If for example, the total system lifetime is 25 years (common lifetime of PV systems) while the expected lifetime of a lead-acid battery in a SHS can be as low as three years, then the battery will need a replacement every three years. For the replacements the battery costs need to be included while accounting the future battery prices, always depending on the technology, dynamically. Thus, lifetime costs take into account parameters such as battery aging and number of replacements. In the case of the hybrid battery the different battery sizing proportions for the different technologies also need to be considered.

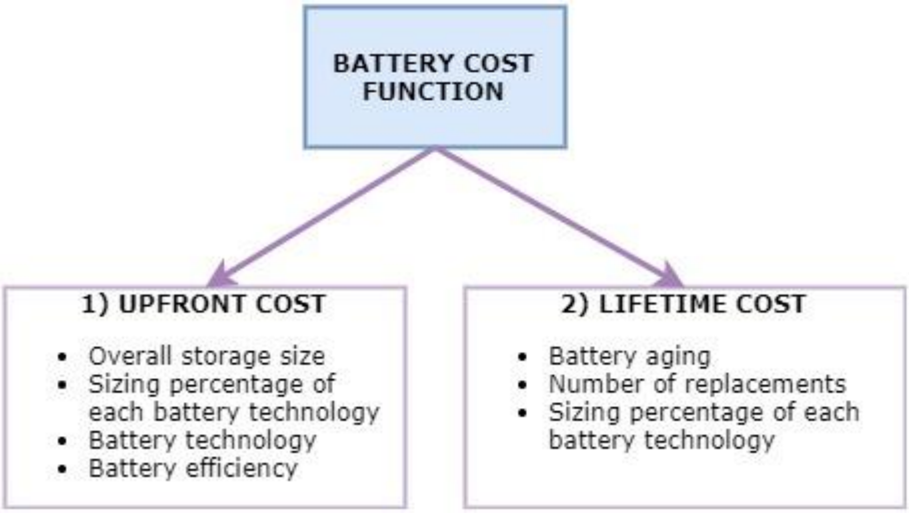


Figure 6-3: Brief representation of the factors included for the construction of the cost function

6.4.1.1. Construction of the Cost Factor – C (t)

The first step taken for the construction of the cost function is the construction of the cost factor which captures the different battery technology costs/kWh. In order to be able to capture future battery costs along with the current prices the cost factor was used. The cost factor is a variable that changes with time and uses learning cost curves for different battery technologies. In general learning curves are able to depict the cost as a function of increased cumulative production and are considered as the most objective method of calculating the future cost trends of different technologies [78]. For these learning curves to be constructed many factors that depict the cost are taken into consideration such as historical data, sales, R&D, cumulative production.

In general, the collection of this kind of data for all the battery technologies used in this project was very difficult and time consuming. While many experience curves representing the trends of Lithium ion batteries were easy to be found, for lead-acid and NiCd batteries, it was very difficult. In addition, when comparing the different Li-ion trends there was observed a discrepancy between them making this procedure even more difficult.

The cost factor is represented as a lookup function which is a fitting of the cost learning curves for different battery technologies as have been found from many economic reports and studies. The general battery cost trends were discussed in detail at the beginning of this chapter. The main observation is that while all of the battery technologies present a downward cost trend, lithium ion shows the steepest decrease in the past years, something that is foreseen to be continued in the future.

- ***Lithium ion and Lead acid learning curves***

For lithium-ion and lead acid batteries the curves decided to be used were retrieved from O. Schmidt et al. paper shown in Figure 6-4. It is worth pointing out that the learning curve representing lithium ion battery cost for electric vehicles shows a much more downward decrease than the one representing lithium-ion battery for residential purposes. The responsible factor for this difference is the current as well as predicted use of lithium-ion batteries in the EV applications. While for EVs it is predicted that this technology will be used broadly, for residential purposes it is not going to be used as much. In other words, the most cost - competitive technology is the one that is able to bring the most capacity into the market [78].

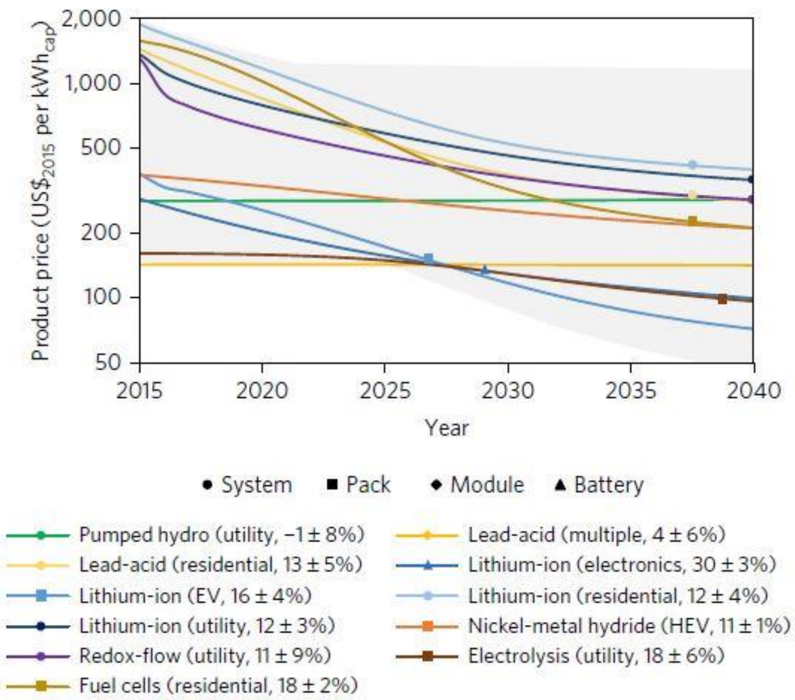


Figure 6-4: Future cost curves of electrical energy storage as a function of time [as shown in [78]]

- ***NiCd learning curve***

For NiCd batteries learning curves were impossible to be found, so the curve was approximated by the author taking into account past and present cost data for NiCd as well as future production rate and use. A cost curve from NiCd cells was found from a report of Swedish Environmental Protection Agency with cost data from 1999 to 2006. That curve showed a non-significant price decrease of NiCd battery cost between this time period starting from 800 $/kWh and after a lot of fluctuations reaching a little less than 600 $/kWh. Another important consideration that was taken into account for the construction of the learning curve for the NiCd batteries is that this technology has started to be more or less replaced by NiMH batteries due to the damaging and toxic effects that the cadmium has to the environment as well as to health [80]. Even though NiCd batteries were broadly used in solar applications having as their main advantage their low cost, their hazardous material combined with the fact that the cost of NiMH batteries was decreased considerably, has made them banned from European Union regulations of hazardous substances [81]. Another report shows that the use and utilization (in volume) of NiCd batteries decreases by 2% every year while Li-ion batteries increases by 21% and NIMH also increase by 6% per year from 1995 to 2015 [82]. The broad use of a battery technology is directly proportional to the cost reduction of this technology, so not using NiCd batteries does not demand for their cost to be reduced. Figure 6-5 shows the global sales of rechargeable batteries between 1991 and 2007 and it is clear that NiCd battery usage is decreasing more than any other battery technology. The cost learning curve that was constructed and approximated for the NiCd batteries takes into account all of the above as well as current cost values of this battery technology [20].

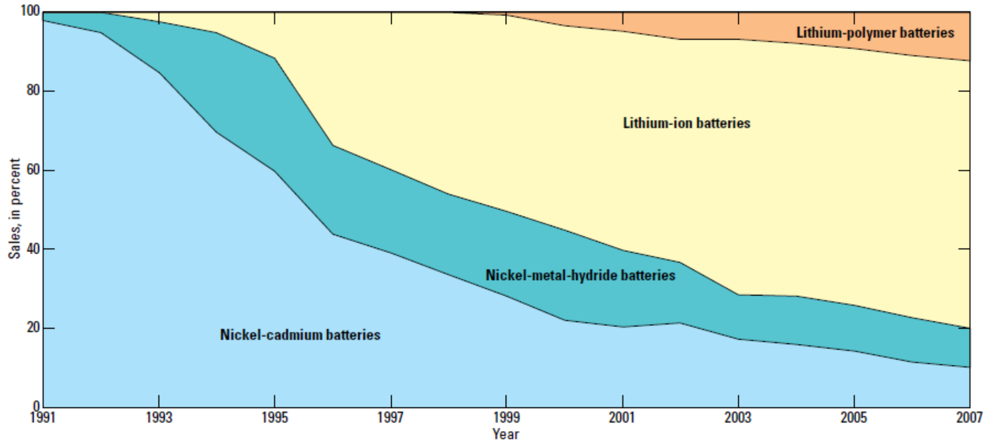


Figure 6-5: Worldwide sales of different technologies of rechargeable batteries from 1991 to 2007. The values represent a percantage f the total global sales of these technologies [as shown in [83]]

One last consideration for the construction of the cost curves for all technologies was the lower cost limit that they could reach in the far future if they continue following the downward trend presented in the curves in Figure 6-6**.** This lower cost limit was decided to be equal to 100 $/kWh after considering many general storage cost predictions found from the literature [75] [84] .

- ***Resulting cost factor curves to be used in the cost function***

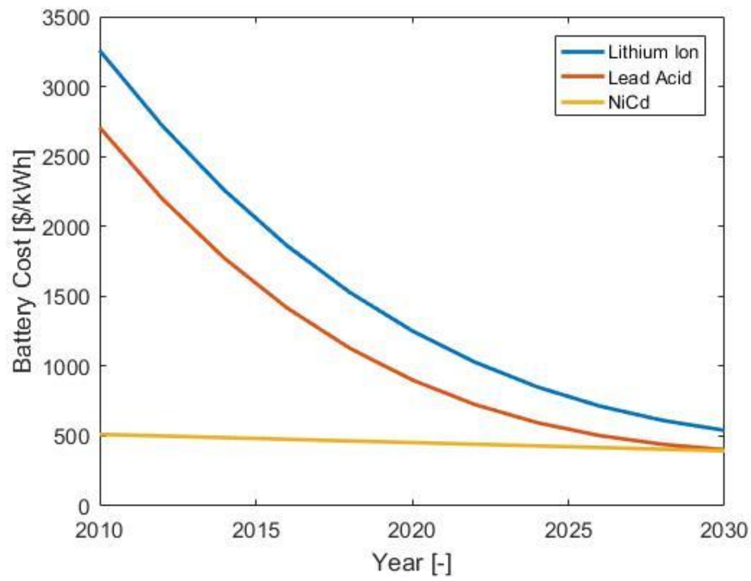


Figure 6-6: Reconstructed cost function curves [sourced from [78]]

The cost function curves shown in Figure 6-6 are the reconstruction of the fitting equations constructed from the curves that were found from literature for lithium ion and lead acid, as well from the NiCd curve constructed by the author.

6.4.1.2. Cost function definition and equations

Two different cost functions were constructed for this study. The first one is for the calculation of the combined upfront and lifetime costs, for individual battery technologies while the other one is for the Hybrid battery systems where a combination of two different battery technologies with a varying sizing proportion is going to be considered. This way, the comparison of the hybrid technology with the individual technologies will be easy and possible using the cost function as a reference.

Battery Cost Function (b.c.f)

Individual Battery Cost Function (b.c.f) is defined as a comparison measure between different battery technologies taking into account their upfront cost and lifetime characteristics for a predefined system lifetime. The units of this function are in $. This function becomes smaller for technologies that present better combination of upfront and lifetime cost results.

$$b.c.f = S * \ C(t_0) + R * S * C\left(t_0 + t_{repl}\right) \tag{6.1}$$

Where,

- $\boldsymbol{b.c.f}$:individual battery cost function[$]
- $\boldsymbol{S}$**:** Storage Size $[kWh]$
- $\boldsymbol{C(t)}$**:** Cost factor at a specific year $[\frac{\$}{kWh}]$,will be explained before
- $\boldsymbol{R}$**:** Number of Replacements $[-]$
- $\boldsymbol{t_0}$: the year that the implementation of the system started
- $\boldsymbol{t_{repl}}$**:** the number of years needed for a battery to reach EOL.

Using the function above, the different battery technologies that were used in this project, can easily be compared in terms of lifetime - performance cost resulting to the best one to be used in the application of Solar Home Systems.

Hybrid Battery Cost Function (h.b.c.f)

Hybrid Battery Cost Function (h.b.c.f) is a comparison measurement between different hybrid battery storage choices consisting of two different individual battery technologies. This function becomes smaller as the technology combination and sizing configuration of the hybrid battery has better lifetime and cost characteristics for a predefined system lifetime.

$$h.b.c.f = \sum_{i=1}^{N} r_i * S_i * C_i(t_0) + \sum_{i}^{N_f} r_i * R_i * S_i * C_i\left(t_0 + t_{repl}\right) \tag{6.2}$$

Where,

- $\boldsymbol{h.b.c.f}$**:** hybrid battery cost function [$]
- $\boldsymbol{r}$**:** percentage of the total size possessed by each of the two technologies,
- $\boldsymbol{N}$**:** Number of technologies used
- $\boldsymbol{N_f}$: Number of failed butteries of each technology

Using the hybrid battery cost function (h.b.c.f) we are able to compare different hybrid storage combinations using different sizing ratios of the different technologies as well as comparing the hybrid storage solutions with the individual technology solutions that used the previous cost function (b.c.f). It is worth pointing out that while the overall size of the storage is the one that was calculated in Chapter 3, for the hybrid system each technology will possess a percentage of this total size.

6.5. Application of Cost Functions

In order to be able to retrieve battery cost function results for the comparison of the different individual battery technologies with the HB storage options, the non-empirical dynamic lifetime estimation method (explained thoroughly in Chapter 4 for the individual technologies and Chapter 5 for the HB storage) was applied into a system lifetime of 25 years.

More specifically, for individual battery technologies, the batteries begin cycling with architecture 1. The dynamic capacity fading model is applied for every ZCs micro-cycle that the battery undergoes, and a check whether EOL was reached is made. If this is the case the battery is replaced with a fresh one having the optimum battery capacity depending on the case study examined, as calculated with the sizing methodology in Chapter 3. This procedure is repeated until the 25 years of the system lifetime are passed. The number of battery replacements that occurred in these 25 years of system operation, the future cost trends of the battery as captured by the battery cost factor curves and the battery sizing are fed into the b.c.f.. The b.c.f is applied, calculating upfront cost for the first time the battery was used and lifetime cost for the replacements needed. The cost function is applied after taking into consideration how many years have passed from the first time that the battery was used (year 2017) until the replacement, in order to be able to capture dynamically the cost of the battery in the future, reaching to more accurate results and conclusions.

In the case of the Hybrid battery storage system the same methodology is applied. The sizing of the two batteries forming the hybrid battery is determined as shown in Chapter 5. The batteries start cycling simultaneously either with PM A or PM B. Dynamic capacity fading is applied to each one of the batteries after a micro-cycle of two zero crossings is found. When one or both of the batteries has reached EOL, it is replaced by a fresh one having the same size as the beginning. This procedure is repeated for both batteries for a system lifetime of 25 years. After this time is passed, the number of replacements each one of the batteries needed, the future cost trends for of the batteries and their proportional to the optimum capacity size are fed to the h.b.c.f. This function is calculated for every HB configuration given.

The combination of the power managements explained in Chapters 3 and 5, the dynamic capacity fading model explained in Chapter 4 and the two cost functions explained in this chapter for a system lifetime of 25 years, is illustrated in detail in the block diagram of Figure 6-7**.**

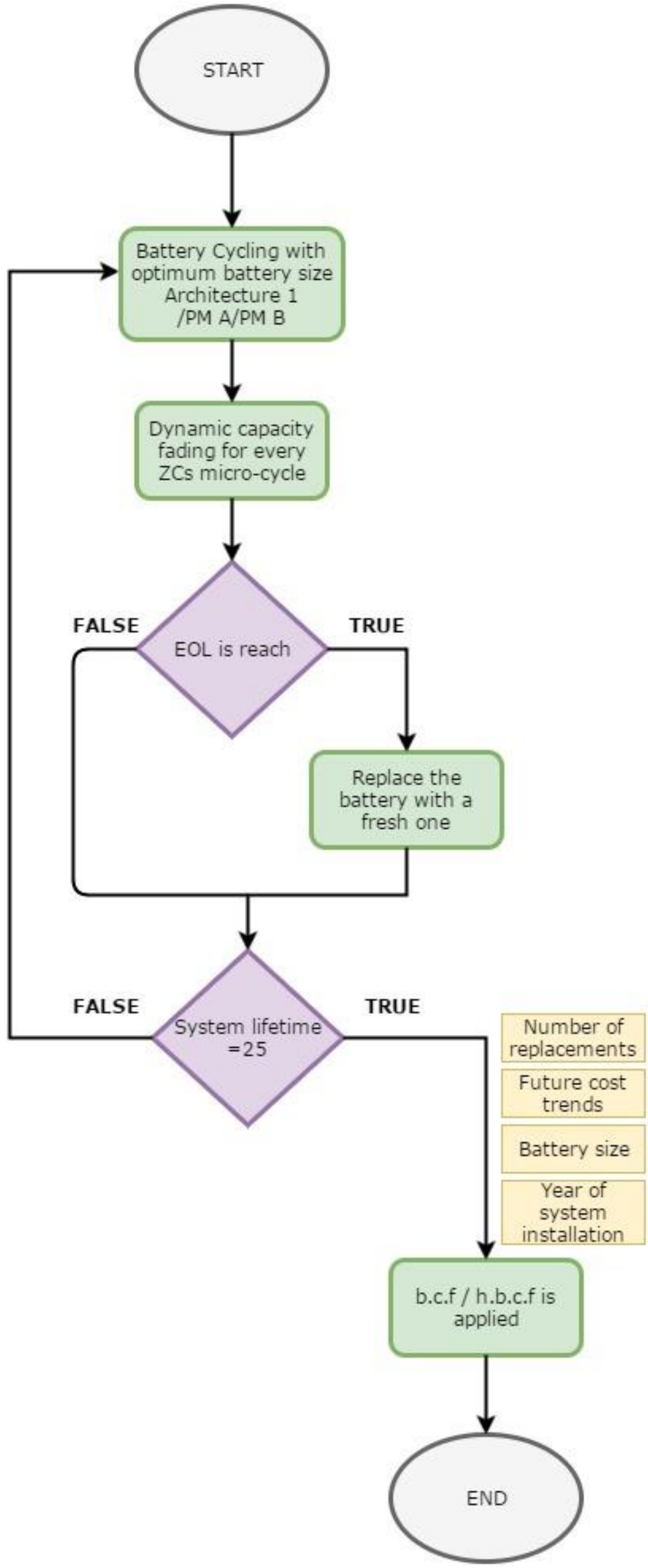


Figure 6-7: Application of dynamic capacity fading and battery cost functions for a system lifetime of 25 years.

This procedure was repeated for two load cases, two power management algorithms, all the different sets of battery technology combinations and variety of different HB ratios. This method was also applied in individual battery technologies for a system of a 25 year lifetime, using energy management of Architecture 1 in order to be able to compare the individual technologies to the use of hybrid battery configurations using the battery cost function and the hybrid battery cost function, respectively.

All the cases that were examined and all of the results obtained are shown in Figure 6-8. The yellow and purple boxes represent the combinations for which case studies 1 and 2 were used while the pink and light blue shadows represent the cases where power management A and power management B were used, respectively. As it can be seen, all the batteries and different sizing combinations were used for both case studies and power management A while for power management B only half of the HB ratios were used.

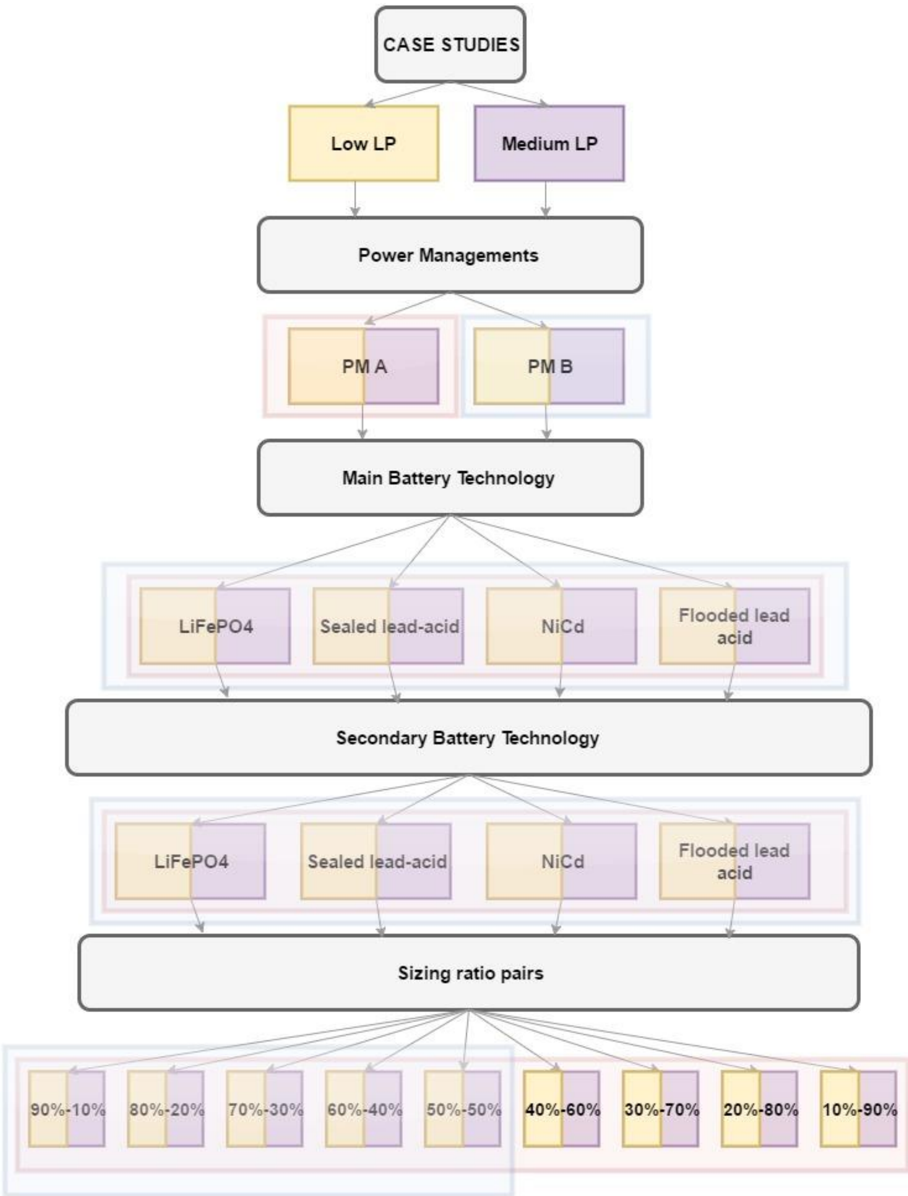


Figure 6-8: All the different cases and combinations that were taken into account

6.6. Results of battery cost function for individual technologies

The obtained results for Case studies 1 and 2 using the optimum battery sizes decided in Chapter 3, 370 Wh and 1150 Wh respectively for System lifetime are shown in Table 15 and Table 16**.**

Table 15: Battery Cost function results (b.c.f) for individual battery technologies for Case Study 1 (low LP)

Battery Technology	b.c.f [$]	Number of replacements	Upfront Cost [$]	Lifetime Cost [$]
Sealed lead-acid	2.84e+03	13	4.68e+02	2.37e+03
Flooded lead-acid	3.45e+03	16	4.68e+02	2.98e+03
NiCd	6.91e+03	46	1.74e+02	6.73e+03
LiFePO4	1.29e+03	3	6.24e+02	6.70e+02

Table 16: Battery Cost function results (b.c.f) for individual battery technologies for Case Study 2 (medium LP)

Battery Technology	b.c.f [$]	Number of replacements	Upfront Cost [$]	Lifetime Cost [$]
Sealed lead-acid	6.52e+03	9	1.45e+03	5.06e+03
Flooded lead-acid	7.22e+03	10	1.45e+03	5.76e+03
NiCd	1.15e+04	24	5.42e+02	1.09e+04
LiFePO4	3.32e+03	2	1.94e+03	1.38e+03

From both case studies, it can be seen that the battery with the higher lifetime is LiFePO4 needing two or three replacements in the period of 25 years that the lifetime of the system is. In addition, it can be seen that the battery cost function is being minimized for LiFePO4 batteries even though their upfront cost is higher than the other technologies. Their high upfront cost is mitigated by their lifetime cost which is lower that all the other technologies, as their lifetime is higher and their cost is being decreasing as the time passes as illustrated better in Figure 6-12. The second best technology is found to be Sealed-lead acid battery having the second smaller battery cost function which is very close to the cost function of the flooded lead acid technology. Lastly, the NiCd battery is found to be the worst technology in terms of combined lifetime costs with the higher battery cost function. Even though, the upfront cost of NiCd batteries is the smallest of the all the technologies their lifetime cost is the higher as they need a very big number of replacements. Histograms illustrating the battery cost function results of each technology as well as the upfront and lifetime costs separately for both case studies are shown in Figure 6-9 to Figure 6-12.

In terms of comparing the different case studies, it can be seen that while the same trends are being followed by the battery technologies, the battery lifetime is lower in Case study 1, thus the batteries need more replacements. The battery cost function though is smaller as the battery size in Case study 1 is almost three times smaller than Case study 2, thus cost/kWh is much smaller.

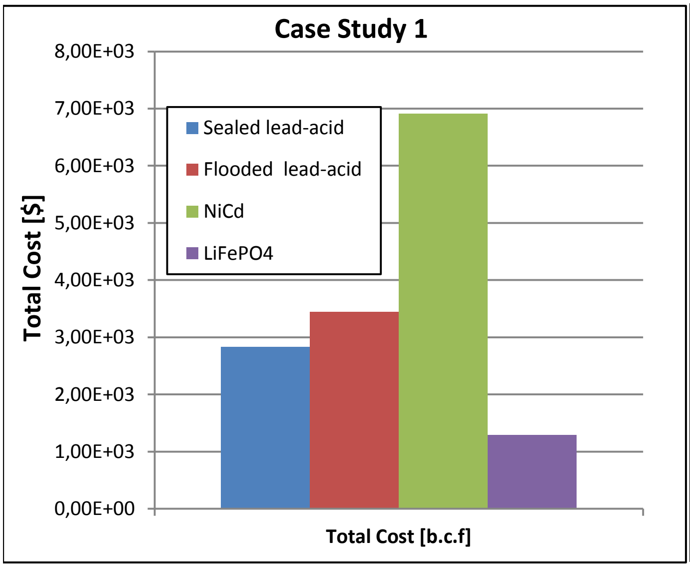


Figure 6-9: Total Battery Cost as derived from b.c.f for all the technologies for Case study 1 (low LP)

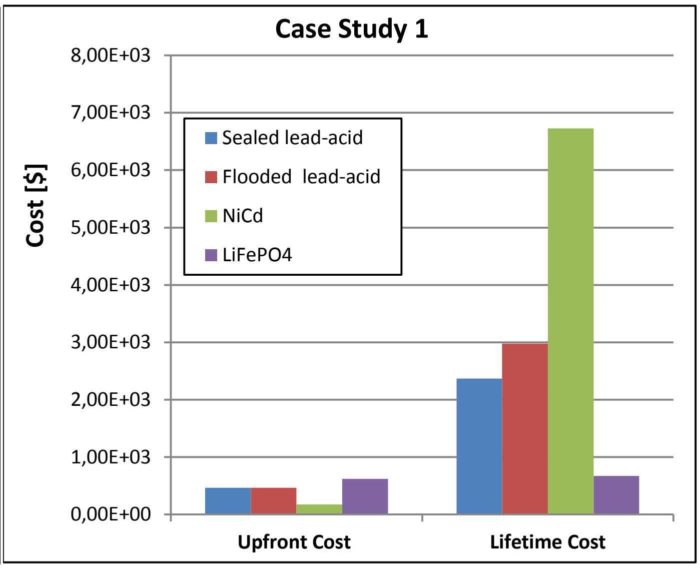


Figure 6-10: Upfront and Lifetime Cost for all the technologies for Case study 1 (low LP)

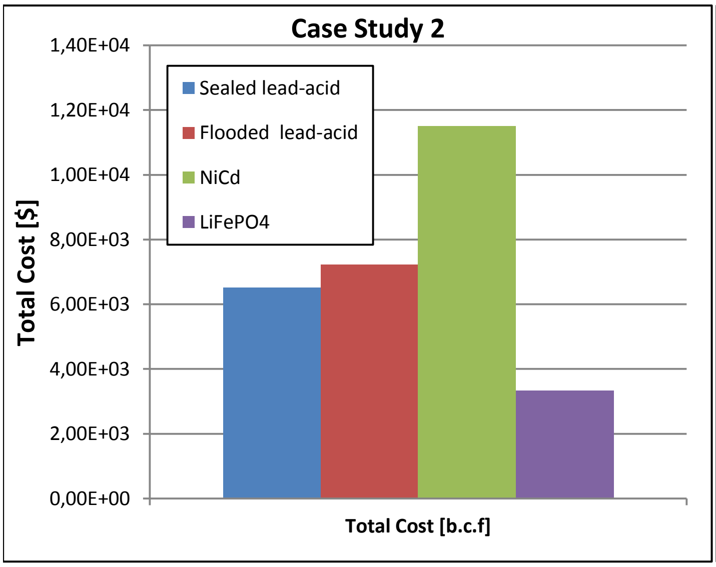


Figure 6-11: Total Battery Cost as derived from b.c.f for all the technologies for Case study 2 (medium LP)

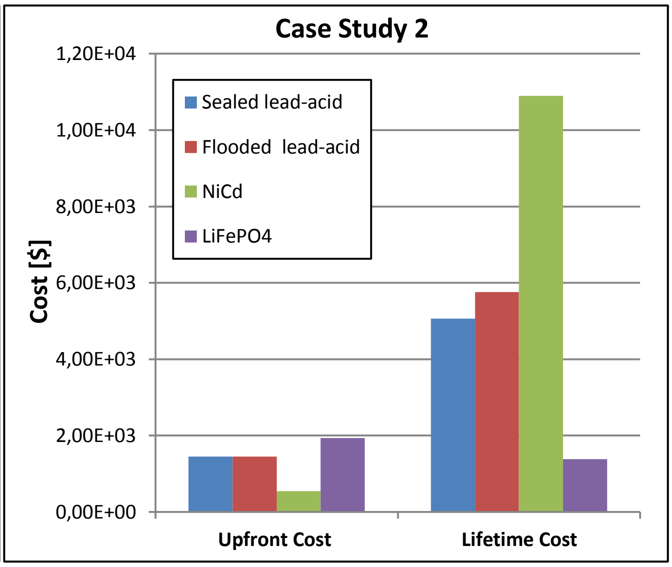
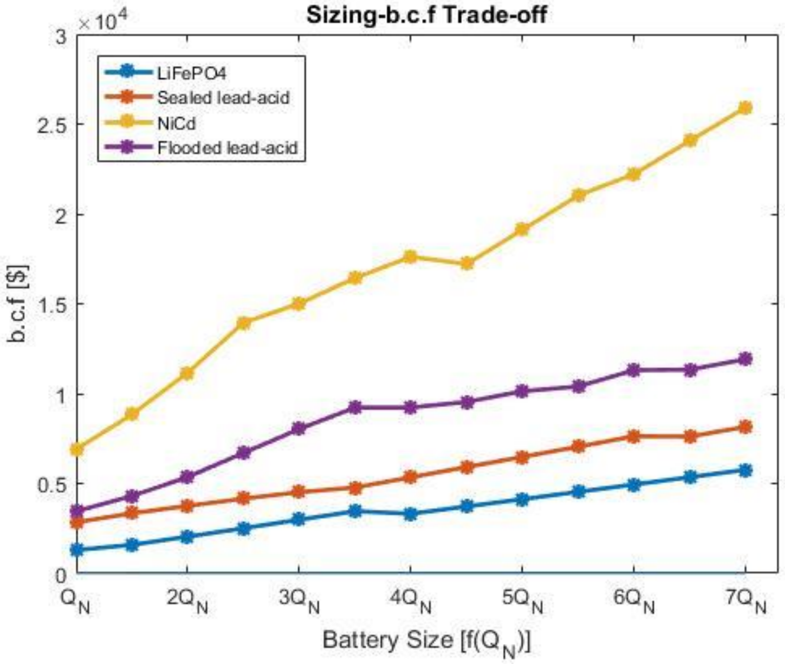


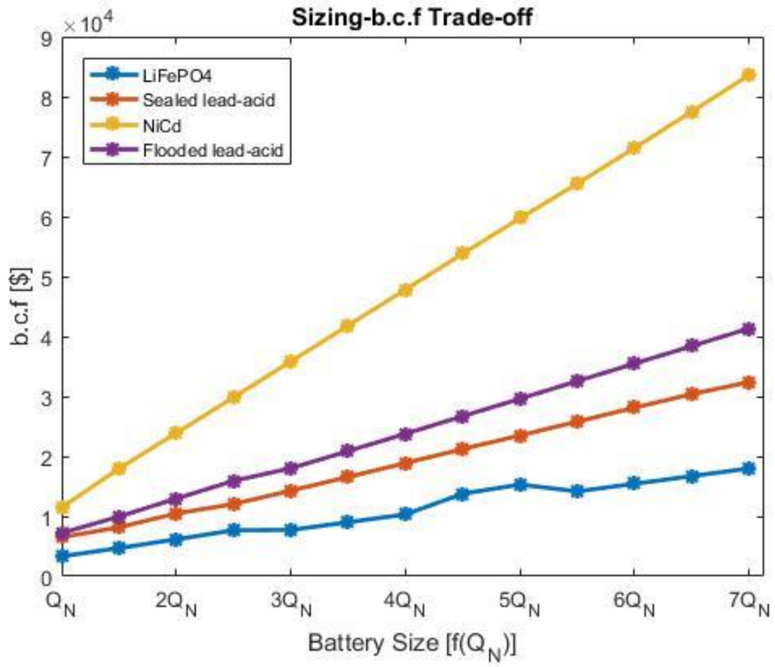
Figure 6-12: Upfront and Lifetime Cost for all the technologies for Case study 2 (medium LP)

6.6.1. Battery Cost Function and sizing trade-offs

In order to examine whether oversizing the battery would have a better result in battery cost function due to increasing battery lifetime, measurements of the b.c.f were made for different battery sizes for all the technologies. The results are shown in Figure 6-13, where Q_N represents the nominal capacity size of the battery.



(a)

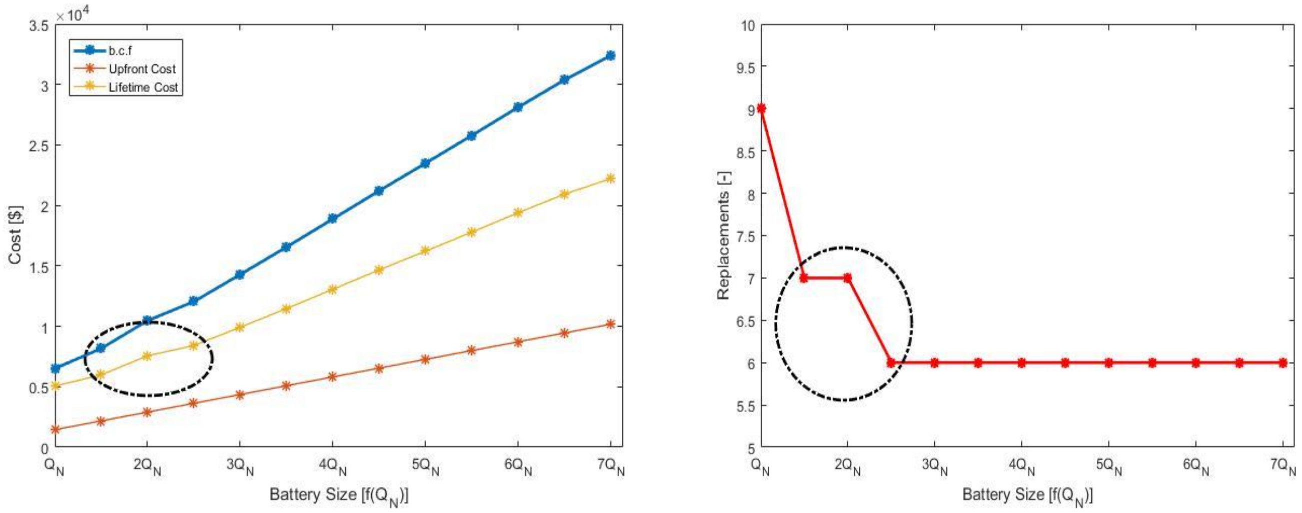


(b)

Figure 6-13: Battery cost function (b.c.f.) and sizing trade-off for (a) Case Study 1 and (b) Case Study 2. C_N represents the nominal capacity of the battery.

It can be seen that while the battery is oversized the b.c.f is increasing. This is logical up to a point as the battery costs are proportional to the battery size. However, after a trade-off point the lifetime of the battery will have to be increased significantly as the battery is oversized. Thus the number of replacements would have to be decreased as well as the lifetime cost which is considered to be the higher cost of the battery.

However, this is not entirely the case. The different lifetime costs and the battery replacements of Sealed lead-acid battery were plotted together in order to be able to examine better the battery behavior as its capacity is oversized. From Figure 6-14, it is seen that the replacements decrease from 9 to 7 when the battery capacity is 1.5 times bigger than the nominal capacity (symbolized in the figure as Q_N). Even though the battery lasts longer the increase in the size is not able to compensate the decrease in the replacements, thus the lifetime cost increases. Going even further, and as the battery is oversized by two times more it is seen that the same number of 7 replacements are needed and this is translated by a steeper slope in the increasing lifetime curve as it is proportional only to cost. After that, and as the battery is oversized even more, the replacements decrease to 6 per year and they remain at this level. In order for the replacements number to start decreasing again the battery needs to be oversized a lot, something that does not help the overall cost to decrease.



(a) (b)

Figure 6-14: (a) Different battery costs for Sealed lead-acid as the battery capacity is oversized, (b)number of required replacements as the battery is oversized

It is worth pointing out that this is the case for almost all the battery technologies depending to the Case study. The number of replacements decreases up to a point and then they more or less remain constant for logical battery sizes.

6.7. Sensitivity Analysis

A sensitivity analysis needs to take place at this point of the project in order to investigate how the results of the battery cost function are going to change in terms of the future battery costs. There is a high uncertainty to whether the battery costs are going to follow the trends that have been used in the learning curves for the cost factor. A small change in the future costs might create a change in the battery cost function which might lead to change in the final battery technology decision making result.

Thus, it is important for a sensitivity analysis to be carried, determining how a change in the cost curve will affect and change the cost function result. For this sensitivity analysis one of the battery technology curves that are included in this project was used. The learning curve that was used is the one for Lithium ion batteries mainly because this technology is foreseen to have the more dramatic decrease over the next years having very optimistic forecasts. In addition, while most of researches and forecasts show that the price of lithium ion battery is going to be decreased drastically over the next years, there are some that disagree. The limited supply of lithium mineral which is concentrated and produced in specific regions all combined with the increased demand of the material have increased its price over the past fifteen years. It is also foreseen that this increase will continue even further as this material is broadly used in the electric car industry with companies such as Tesla, Apple to Google to try and launch new and more efficient lithium batteries for EVs. Having all these in mind, lithium carbonate price has shown a price increase of 47% over the past two years [85]. This is also shown in Figure 6-15.

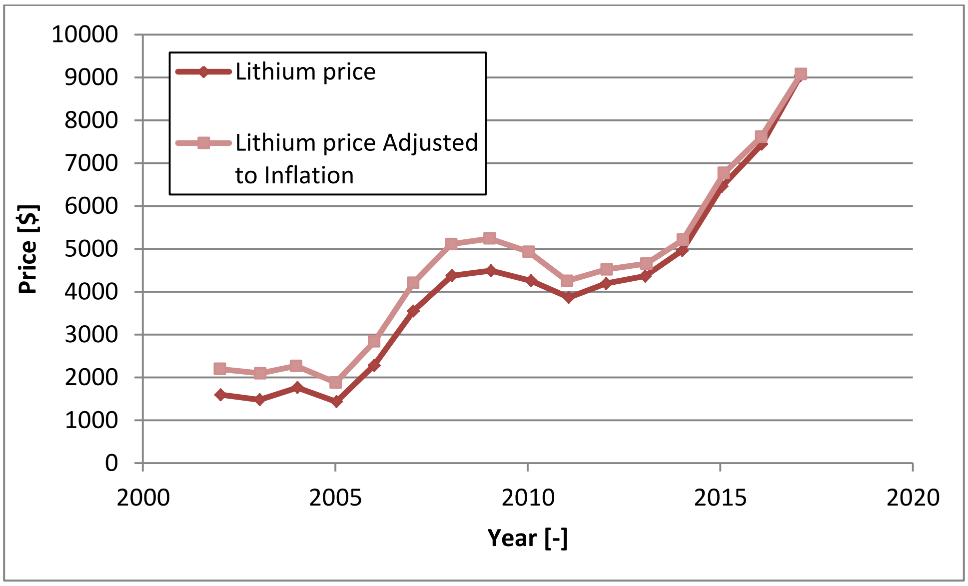


Figure 6-15: Lithium Carbonate Price increase from 2012 to 2017 [data sourced from [85]]

For the sensitivity analysis three different curves were conducted and used. The first one represents the worst case scenario where the Li-ion cost remains the same as its present value experiencing zero reduction. The other two curves represent in between offset curves between the worst case scenario and the curve that is already used representing the most optimistic scenario. These curves are shown in Figure 6-16.

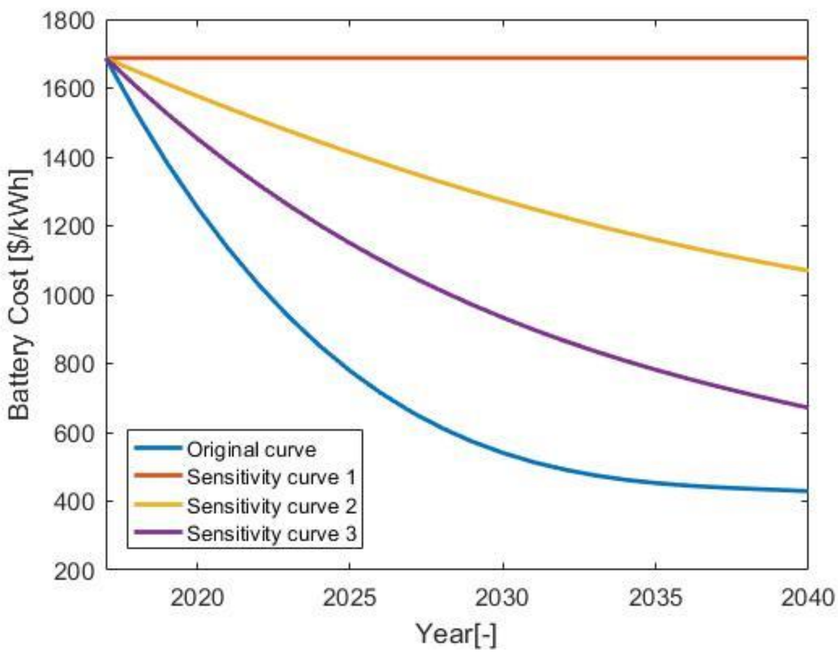


Figure 6-16: Lithium Ion battery price curves used for the sensitivity analysis

Using all of the curves shown above, the simulation for LiFePO4 for a System lifetime of 25 years and for one load profile (medium LP) was run and the battery cost function was applied for all three sensitivity curves. The upfront and lifetime cost for each case were calculated for the same battery lifetime and the same number of replacements as well as the overall battery cost function. Figure 6-17 includes projection curves at the year points that the battery needed replacement and the cost per kWh used on each sensitivity case.

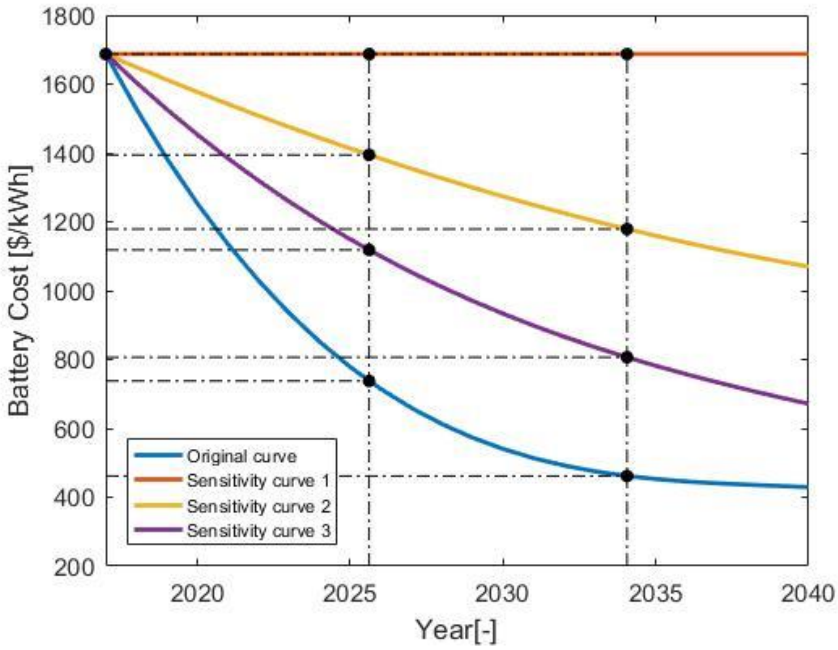


Figure 6-17: Lithium Ion battery price curves used for the sensitivity analysis including the projection price curves in the years of the battery replacements

The replacements occur in years 2025.6 (x1) and year 2034.1(x2) as shown by the projection lines in the x-axis of Figure 6-17. It is seen that the battery needed two replacements, every almost 8.5 years starting from 2017. It is also clear that there is a significant difference in the price between the sensitivity curves and the original curve. In addition, it is worth pointing out that the upfront cost in each case is the same as it represents the price per kWh of Lithium-ion battery in the present (2017) and that is why all the curves have the same starting point. The results of the sensitivity analysis including the difference that occurs in the lifetime cost differently for every replacement and the resulting h.b.c.f difference are summarized in Table 17.

Table 17: Sensitivity analysis results for upfront lifetime and overall cost (b.c.f) for all the cases

Curve	Upfront Cost [$]	Lifetime Cost [$]		Input Difference from original curve		b.c.f [$]	Output Difference from original curve
		Year of replacements					
		x1	x2	x1	x2		
Original curve	1.94e+03	848.34	530.99	-	-	3.32e+03	-
Sensitivity curve 1		1940.30	1940.30	128.72%	265.41 %	5.82e+03	75.30 %
Sensitivity curve 2		1603.40	1355.80	89 %	155.33 %	4.90e+03	47.59 %
Sensitivity curve 3		1285.80	927.4	51.57 %	74.65 %	4.15e+03	25 %

The last column of Table 17 shows the percentage difference of the b.c.f calculated using the original curve with the b.c.f calculated using each one of the sensitivity curves while the fourth column shows the percentage difference of the input values for every year of replacement. As expected, the difference between the original and the worst case scenario curve (sensitivity curve 1) is very significant reach about 75 % while the other two sensitive curves present a difference of 47% and 25% accordingly. The overall conclusion of the sensitivity analysis is that a difference in the future cost of the batteries can lead to a very different cost function able to affect the overall result of battery technology selection for a specific application such as SHS.

6.8. Results of hybrid battery cost function for HB configurations

6.8.1. **Power Management A (PM A)**

6.8.1.1. Case Study 1

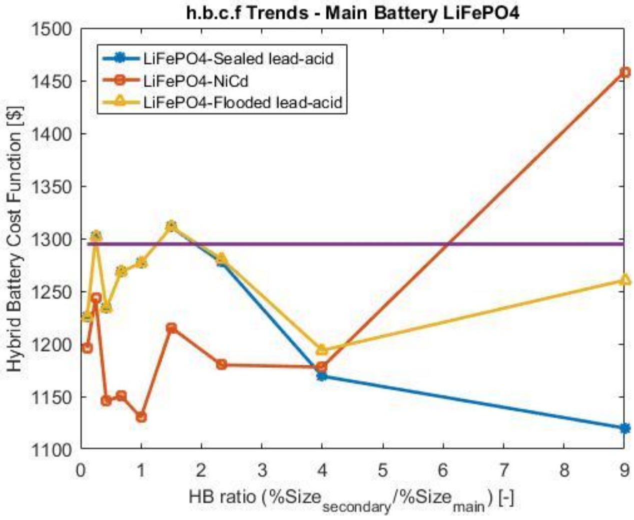
The results for the hybrid battery cost function power management A when varying the battery sizing percentage from 10 to 90 with a step of 10 Wh, for all different battery technology combinations, are shown in the Appendix A Table 26for Case study 1.

In Table 26 the technologies that are being with bold and purple background colour represent the main battery technologies used in PM A while the ones under them are the secondary batteries used for that power management. The first two columns of the table indicate the battery size of the main and secondary battery in respect to the optimal battery size that was calculated for Case Study 1 in Chapter 3 and is equal to 370 Wh. For example, when the ratio of the main battery technology is equal to 60% the ratio of the secondary battery technology equals to 40 % of the overall storage size. Thus,

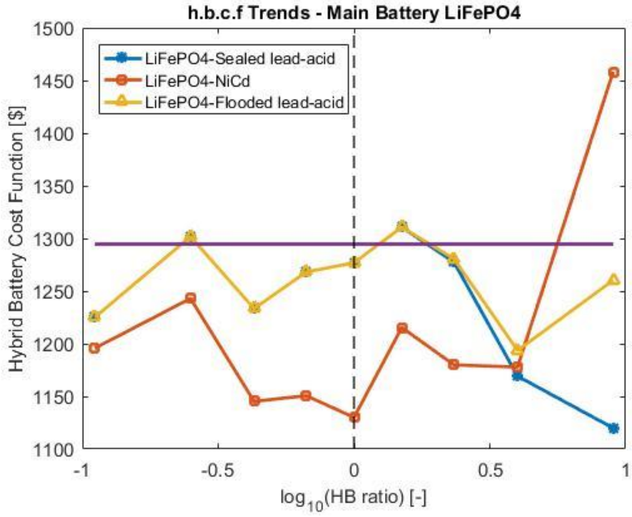
$$Size_{main} = 0.6 \times 370 = 222\,Wh \tag{6.3}$$
$$Size_{secondary} = 0.4 \times 370 = 148\,Wh \tag{6.4}$$

The last row of the table shows the minimum value of the Hybrid battery cost function for every one of the cases. In addition, this value was also highlighted with light blue colour in the table in order to indicate clearer which specific sizing ratio combination minimizes the cost function for every one of the technology combinations.

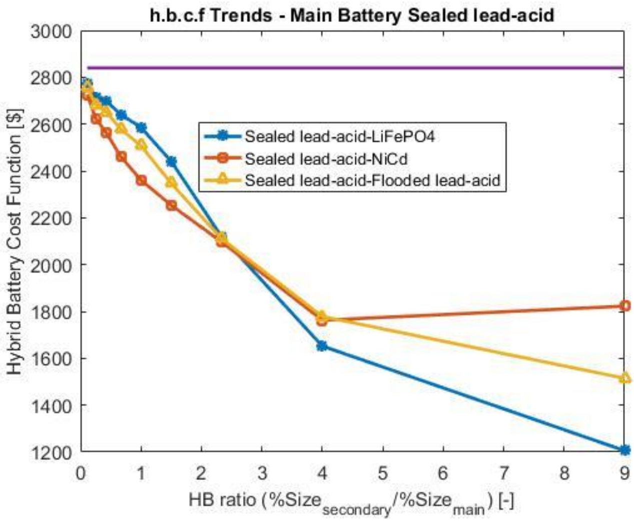
The general trends that were followed from the Hybrid battery cost function calculation can be shown in Figure 6-18 for each one of the battery combination cases, grouped together in figures with the same main battery technology.


h.b.c.f Trends - Main Battery LiFePO4
LiFePO4-Sealed lead-acid
LiFePO4-NiCd
LiFePO4-Flooded lead-acid
Hybrid Battery Cost Function [$]
HB ratio (%Size$_{secondary}$/%Size$_{main}$) [-]

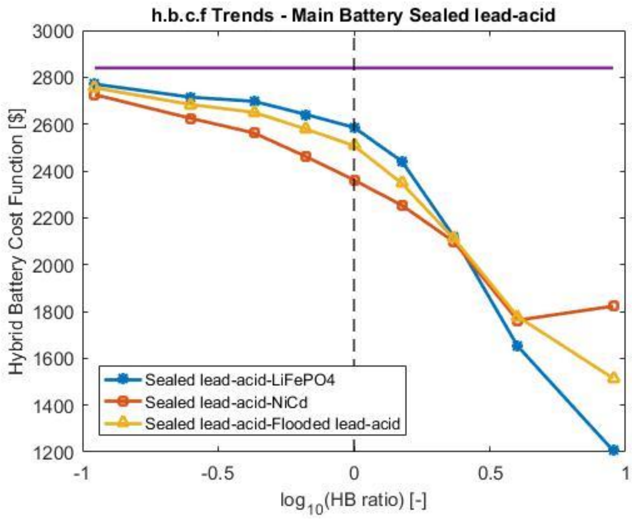
(a1)


h.b.c.f Trends - Main Battery LiFePO4
LiFePO4-Sealed lead-acid
LiFePO4-NiCd
LiFePO4-Flooded lead-acid
Hybrid Battery Cost Function [$]
log$_{10}$(HB ratio) [-]

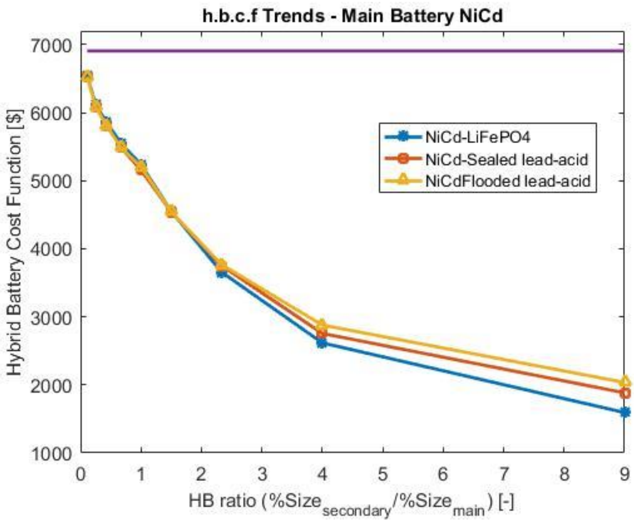
(a2)


h.b.c.f Trends - Main Battery Sealed lead-acid
Sealed lead-acid-LiFePO4
Sealed lead-acid-NiCd
Sealed lead-acid-Flooded lead-acid
Hybrid Battery Cost Function [$]
HB ratio (%Size$_{secondary}$/%Size$_{main}$) [-]

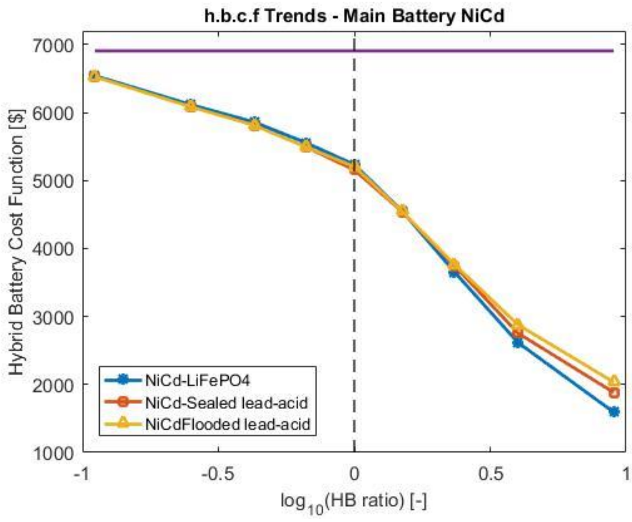
(b1)


h.b.c.f Trends - Main Battery Sealed lead-acid
Sealed lead-acid-LiFePO4
Sealed lead-acid-NiCd
Sealed lead-acid-Flooded lead-acid
Hybrid Battery Cost Function [$]
log$_{10}$(HB ratio) [-]

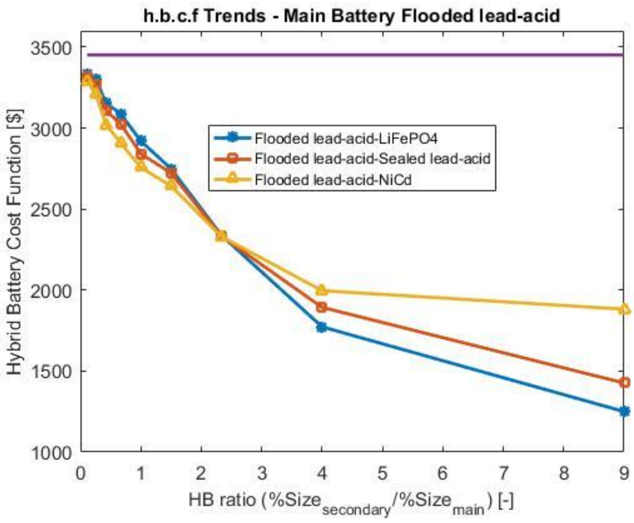
(b2)



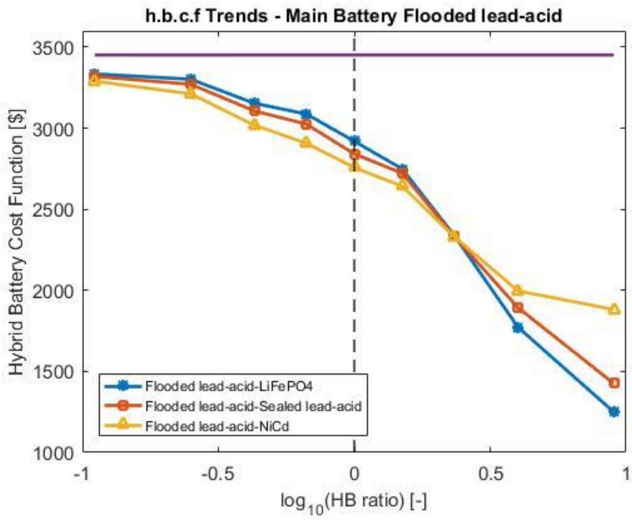
(c1)



(c2)



(d1)



(d2)

Figure 6-18: Hybrid Battery cost function trends for different battery technology combinations, for PM A-Case Study 1. The first column represents the trends in respect to HB ratio. The second column represents the trends in logarithmic scale in respect to HB ratio. (a1-a2)-main battery LiFePO4, (b1-b2)-main battery Sealed lead-acid, (c1-c2)-main battery NiCd, (d1-d2)- main battery Flooded lead-acid. Purple line represents the b.c.f for 100% of the Individual main technology.

Observations from h.b.c.f trends

- In general it can be seen that the HB ratios optimizing the hybrid battery cost function are varying between the different technology combinations. This is mainly due to the varying upfront costs, which are directly proportional to the battery size, thus proportional to the HB ratio in combination with the varying lifetime costs. The lifetime costs are also proportional to the battery size and are defined as the cumulative cost that occurs for all the battery replacements of each technology. If a battery needs to be replaced every three years, the lifetime cost will consider all the times that the battery needed replacement and the future cost that correspond to that time. In addition, efficiency and temperature sensitivity also affect the results of the battery cost function but in a lesser extent. When observing Figure 6-18 some more specific observations can be made:

- To begin with, when LiFePo4 battery (a1-a2) is used as the main technology, there is not a general trend followed by the h.b.c.f. The function fluctuates a lot while the HB ratios are changing and while the secondary technology changes. This fluctuation can be explained by examining the number of replacements and the lifetime cost results**.** It was observed that the replacements of the batteries follow the same trend in all three combinations. At the beginning, when the HB ratio is very small, with lithium ion technology as the main technology to be having a high amount of the overall battery sizing, the secondary technologies do not need replacements throughout the system lifetime. However, as the secondary technology sizing increases decreasing the main technology size, the replacements of the secondary technology start increasing. This increase continues for all follow up HB ratios. The replacements of the lithium ion technology are also increasing up to one point where the HB ratio becomes 4 (thus 20% main and 80% secondary) where it starts decreasing as the secondary technology becomes higher in size than the main and is able to complement the main technology more. The fluctuations shown in the cost function have to do with the lifetime cost of secondary technology combined with the lifetime cost of the main technology as the upfront cost follows the trend that the cost factor curves follow for the specific technologies as it is only depended by the sizing. The results of the replacements can be seen in Figure 6-19.

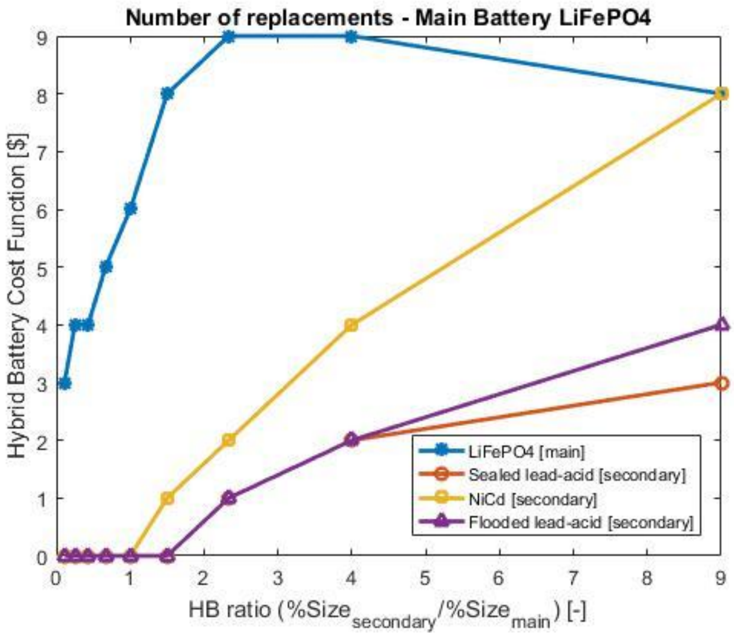


Figure 6-19: Number of replacements needed when LiFePO4 is used as the main battery technology, for all the secondary technology combinations

- It can be seen that when using for storage a single technology of LiFePO4 battery, the battery cost function remains mostly higher than the one calculated for the Hybrid battery. This is mainly due to the high upfront cost that the Lithium Ion technology has, which even though is decreasing as the years are passing, it still remains significantly higher than the other technologies for most of the time. More specifically, after the simulation was done for the 25 System lifetime years, the LiFePO4 battery had to be replaced every almost 7 years of lifetime also shown in Table 17. Thus it needed three replacements overall. When observing Figure 6-6 it can be seen that starting from 2017 the cost of lithium ion battery is much higher than the cost of the other technologies. Continuing for seven years later to 2024 the cost of this technology remains higher and even for seven years after that it still is a little bit higher. Thus, for the first two replacements needed LiFePO4 is more expensive than the other technologies while for the third replacement they almost have the same cost value.

- When sealed lead acid battery is being used as the main technology of the hybrid system (Figure 6-18 b1-b2), there is a general downward trend followed as the sizing of the main battery is decreased and the sizing of the secondary one is increased. Even though, lead-acid batteries in general present a low and decreasing upfront cost, but still significantly higher than the NiCd batteries, their lifetime is not that high mitigating their low cost for the overall b.c.f results. It can be seen that when using a 100% of sealed lead-acid battery the cost function is much higher than the cost function of the HB system. Thus, the downward trend followed when blending it with other technologies is natural. It is clear that the best option using sealed lead acid as the main battery technology is when combining it with lithium ion battery. The curve becomes even steeper as the size of LiFePo4 battery is increased. This is explained by the fact that both of these two batteries follow similar downward trends in their cost function, with LiFePO4 battery to be presenting much higher lifetime than lead acid batteries. More specifically, for the best case scenario in this case, which is shown to be 90% of LiFePO4 technology and 10% of Sealed- lead Acid, the second one needs a replacements for almost every year of the system lifetime while the second one needs only one replacement. This is logical because Sealed Lead Acid, as the main battery is being used constantly while lithium-ion is complementing it in times when it cannot provide the energy needed.

- For the third choice of main battery technology, NiCd (Figure 6-18 c1-c2) a downward trend as the technology is blended with other batteries is also followed. It is evident that when using only NiCd battery, the cost function is significantly higher, and the more NiCd technology is combined with other technologies, the better are the h.b.c.f results. The main reason for that is that even though NiCd batteries appear to have low and constant over the years cost, their lifetime and efficiency is much lower than the lifetime of the other technologies. NiCd technology needs almost two replacements every year, when is used as single technology, making it very unsuitable for Solar Home System applications.

- The fourth technology that was examined as the main battery in Power management A is flooded lead acid batteries. These batteries follow a very similar trend as sealed lead-acid batteries but their general h.b.c.f results are higher than the latter. This has to do mainly with the fact that flooded lead-acid batteries present less roundtrip efficiency than sealed lead acid. In addition sealed lead acid batteries present better tolerance in the temperature effects as can be seen from the reconstructed cycle life – temperature curves of the two batteries in figures Figure 4-2 and Figure 4-3.

- One general observation that can be made is that while specific trends are followed by mostly all of the h.b.c.f in all combinations, there are cases that the last point of the function, when 90% of the overall size is represented by the secondary battery and 10% (HB ratio=9) by the main, that the general trends stops and this point deviates. It is observed that this is happening in the cases where NiCd is used as the secondary battery. This can be explained by the significant increase in the replacements that this technology needs when it goes from 80% of the battery size to 90% , increasing its lifetime cost and thus the h.b.c.f even further.

- When comparing the general results of h.b.c.f it can be seen that using LiFePO4 as the main battery technology, minimizes its value, while using NiCd as the main technology maximizes its value.

In order to be able to compare the best case scenarios of each HB combination separately with the cases where a single technology is used as the storage option in the Solar Home System, the results were grouped and shown Table 18.

Table 18: Best Case Scenarios for all four cases using different main battery technologies, with their optimal corresponding sizing ratio and their minimum h.b.c.f value(PM A – Case study 1).

Best Case Scenarios for Hybrid Battery Cost Function [$]				
Secondary / Main	**LiFePO4**	**VRLA**	**NiCd**	**Flooded**
LiFePO4	1.29 E+03 **[100%]**	1.12E+03 **[10%-90%]**	1.13E+03 **[50%-50%]**	1.19E+03 **[20%-80%]**
VRLA	1.21E+03 **[10%-90%]**	2.84 E+03 [100%]	1.76E+03 **[20%-80%]**	1.51E+03 **[10%-90%]**
NiCd	1.59E+03 **[10%-90%]**	1.88E+03 **[10%-90%]**	6.91 E+03 **[100%]**	2.04E+03 **[10%-90%]**
Flooded	1.25E+03 **[10%-90%]**	1.43E+03 **[10%-90%]**	1.88E+03 **[10%-90%]**	3.45 E+03 **[100%]**

Seeing all of the results above, it can be seen that the configuration that optimizes the h.b.c.f is when using 10% of the overall battery size for LiFePO4 battery and 90% for Sealed lead-acid, with the first one to represent the main battery in power management A. The best case scenario information for Power Management A - case study 1 are shown in Table 19.

Table 19: Optimal Storage choice for PM A and Case study 1

	LiFePO4 [main]	**Sealed lead-acid [secondary]**
Sizing ratio [%]	10%	90%
Size [Ah]	37	333
Number of replacements [-]	8	3
Upfront Cost [$]	62.42	421.12
Lifetime Cost [$]	196.19	440.17
h.b.c.f [$]	1.12E+03	

The different costs for the optimal storage choice presented above are illustrated in Figure 6-20. It can be seen that in general upfront cost is smaller than the lifetime cost as the batteries needed some replacements throughout the system lifetime. More specifically LiFePO4 battery had to be replaced every almost 3 years of operation while sealed lead-acid had to be replaced almost every 7 years of operation. In addition the upfront and lifetime cost of sealed lead acid is higher than the one of LiFePO4 battery, as it is proportional to the battery size, and lead acid is bigger than lithium ion. Even though LiFePoO4 needs more replacements than lead acid, its lifetime cost is being mitigated not only by sizing but also from the decrease that this technology shows in future costs.

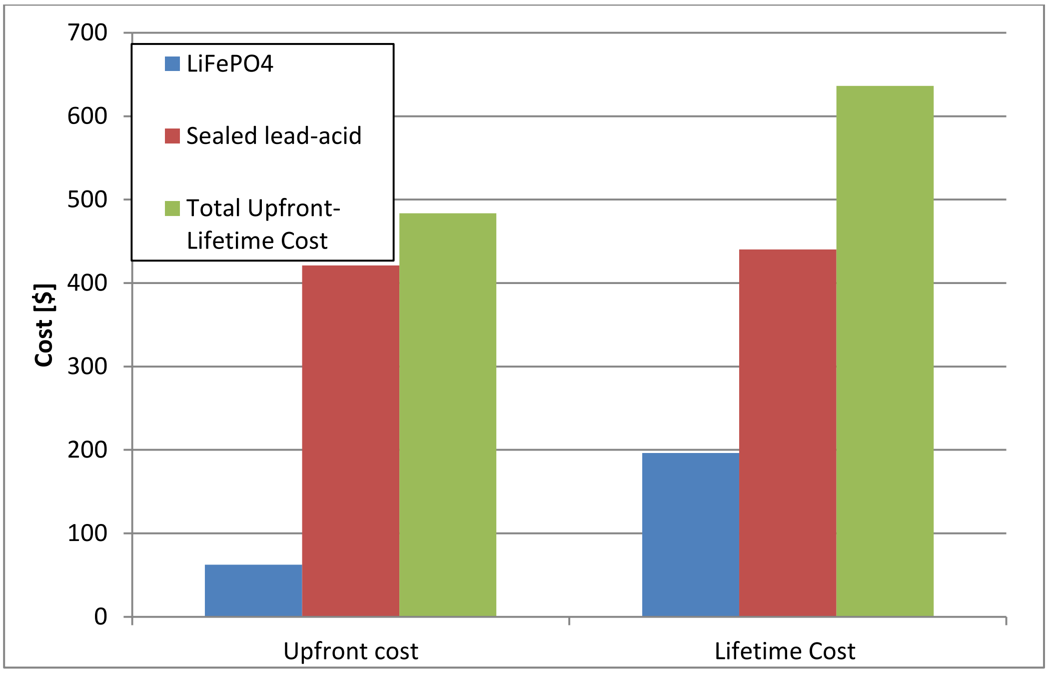
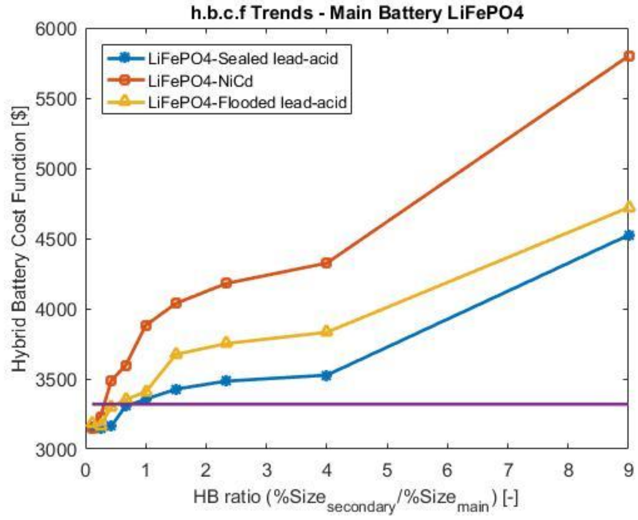


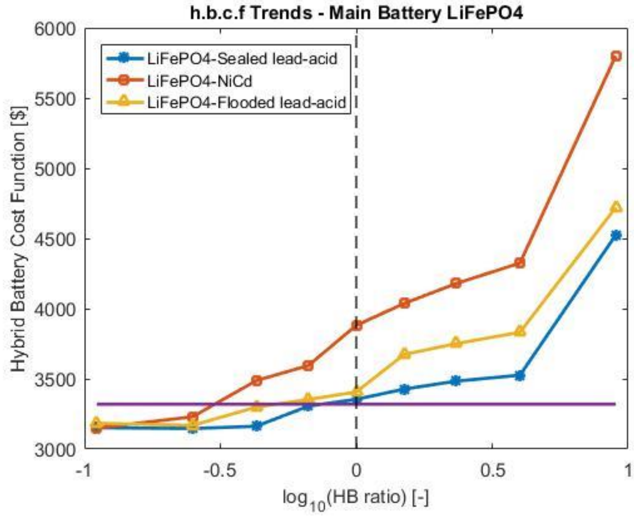
Figure 6-20: Lifetime and Upfront cost for the best Case Scenario in PM A - Case study 1

6.8.1.2. Case Study 2

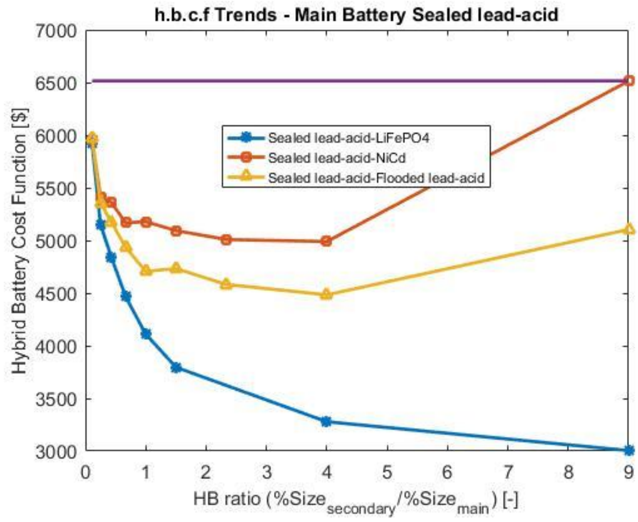
The results for the hybrid battery cost function power management A (main and secondary battery) when varying the battery sizing percentage from 10 to 90 with a step of 10 Wh, for all different battery technology combinations, are shown at Table 27 in the Appendix. The minimum value of each case is shown in the last row of the table. These values are also highlighted with light blue inside the table. The general trends that were followed from the Hybrid battery cost function calculation can be shown in Figure 6-21 for each one of the battery combination cases, grouped together in figures with the same main battery technology.



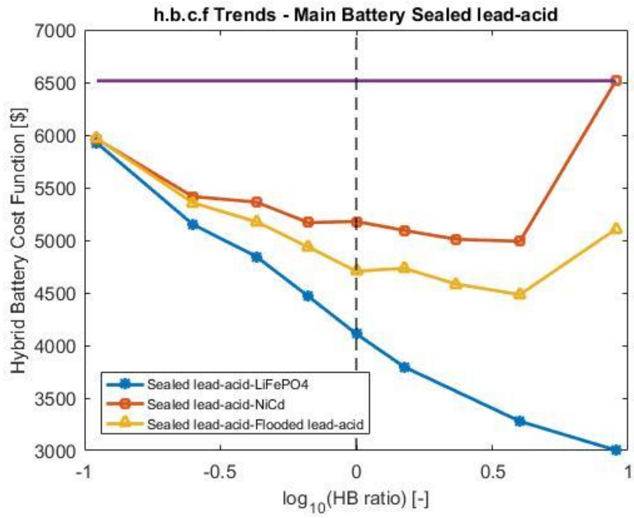
(a1)



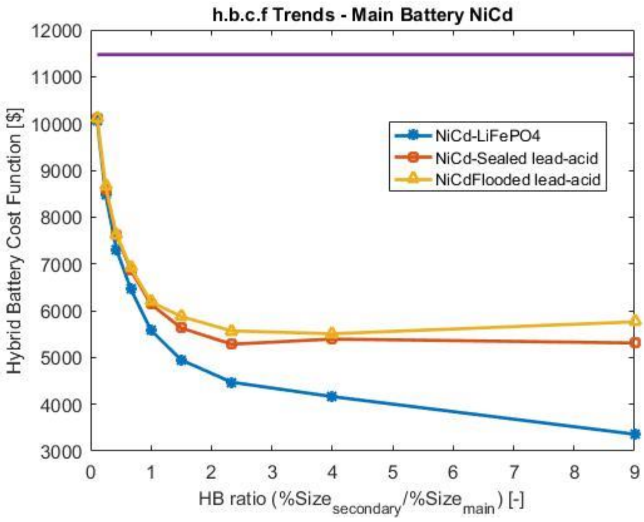
(a2)



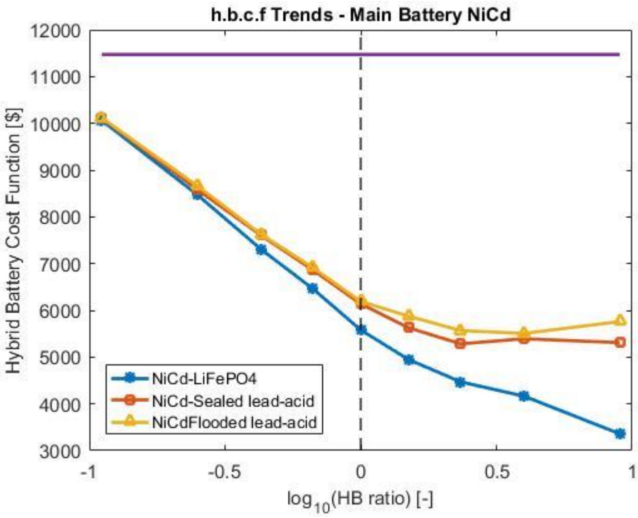
(b1)



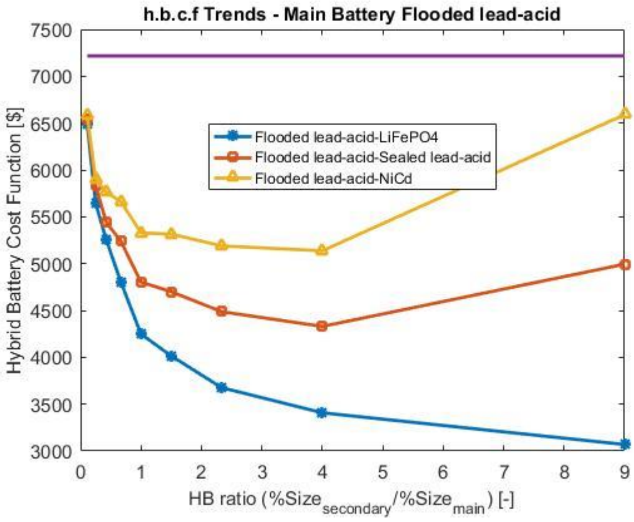
(b2)



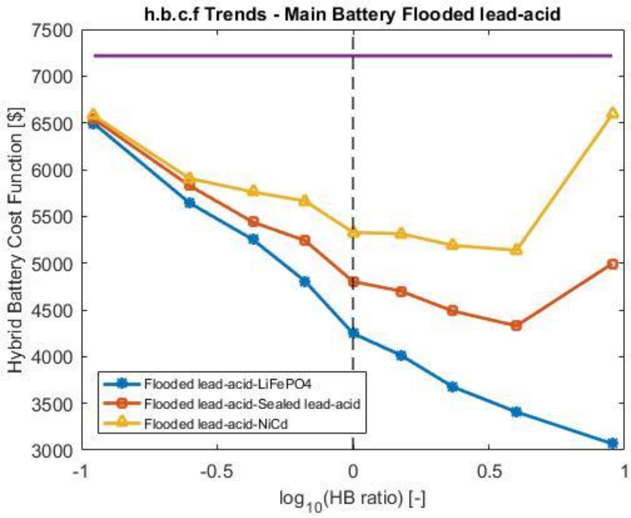
(c1)



(c2)



(d1)



(d2)

Figure 6-21: Hybrid Battery cost function trends for different battery technology combinations, for PM A-Case Study 2. The first column represents the trends in respect to HB ratio. The second column represents the trends in logarithmic scale in respect to HB ratio. (a1-a2)-main battery LiFePO4, (b1-b2)-main battery Sealed lead-acid, (c1-c2)-main battery NiCd, (d1-d2)- main battery Flooded lead-acid. Purple line represents the b.c.f for 100% of the Individual main technology.

Observations from h.b.c.f trends

- From Figure 6-21 many observations can be made. In general, most of the combinations follow similar trends as in Case Study 1. To begin with, when LiFePO4 (a1-a2) is the main technology the h.b.c.f. follows an upward trend while the lithium ion technology is being blended with other technologies. More specifically, as the size of the secondary technology increases, meaning that the size of the main technology decreases, the overall cost of the system becomes larger. It can also be seen that when using 100 % of lithium ion technology the h.b.c.f has relatively low value compared to some of the combinations of the hybrid system. However, when combining the lithium ion technology with cheaper options (secondary technologies) especially when their size is smaller than the size of lithium ion, the h.b.c.f has also smaller value than the cost of occurs for 100% size of lithium-ion. Lastly, it can be observed that again NiCd technology as secondary technology gives the most expensive function and sealed lead acid for small ratios the most cheap.

- When using sealed lead-acid as the main technology (b1-b2), the same trend as in Case Study 1, is followed. As the main lead acid technology is combined with other secondary technologies, the cost function is decreased. The more the sizing of the secondary battery increases the more the cost function decreases, leading for the best option being when adding 90% of LiFePO4.

- Flooded lead acid and NiCd batteries as the main technologies in this power management follow the same trend. While using 100% of these two technologies the system the cost function becomes very large, and when other technologies are added the hybrid battery cost function starts decreasing. The best option for both of these technologies is to combine them with LiFePO4 as the secondary battery. In addition, the general presented cost when using NiCd battery is almost 1.5 times more expensive than the cost presented when flooded lead acid is the main technology. These two batteries have lower efficiency compared to the other technologies decreasing their lifetime and increasing their h.b.c.f results.

In order to be able to compare the best case scenarios of each technology combination separately to the case that a single used as the storage option in the Solar Home System the results were grouped as shown in Table 20.

Table 20: Best Case Scenarios for all four cases using different main battery technologies, with their optimal corresponding sizing ratio and their minimum h.b.c.f value (PM A – Case Study 2).

Best Case Scenarios for Hybrid Battery Cost Function [$]				
Secondary / Main	**LiFePO4**	**VRLA**	**NiCd**	**Flooded**
LiFePO4	3.32e+03 **[100%]**	3.15E+03 **[80%-20%]**	3.15E+03 **[90%-10%]**	3.17E+03 **[80%-20%]**
VRLA	3.00E+03 **[10%-90%]**	6.52e+03 **[100%]**	4.99E+03 **[20%-80%]**	4.48E+03 **[20%-80%]**
NiCd	3.36E+03 **[10%-90%]**	5.28E+03 **[30%-70%]**	1.15 E+04 **[100%]**	5.51E+03 **[20%-80%]**
Flooded	3.07E+03 **[10%-90%]**	4.33E+03 **[20%-80%]**	5.14E+03 **[20%-80%]**	7.22e+03 **[100%]**

Observing all of the results above, it can be seen that the configuration that optimizes the h.b.c.f is when using 10% of the overall battery size for Sealed lead Acid battery and 90% for LiFePo4 with the first representing the main battery in power management A. The best case scenario information for Power Management A - case study 2 are shown in Table 21.

Table 21: Optimal Storage choice for PM A and Case study 2

	Sealed Lead Acid [main]	**LiFePO4 [secondary]**
Sizing ratio [%]	10%	90%
Size [Ah]	115	1035
Number of replacements [-]	11	1
Upfront Cost [$]	145.43	1746.21
Lifetime Cost [$]	610.02	502.98
h.b.c.f [$]	3.00E+03	

The different costs for this best case scenario are illustrated in Figure 6-22. It can be seen that the upfront cost, in general, is higher than the lifetime cost. For LiFePO4 battery this is explained by the fact that it needs only one replacement over the system lifetime accounting for 15 years of operation. For lead acid this is explained by the size of the battery. More specifically, as lead acid possesses only 10% of the overall battery cost its upfront cost is very low and even though it needs 11 replacements throughout the 25 year system lifetime (almost for every 2 years), its small size does not increase the lifetime cost significantly. In addition, it can be seen that the upfront cost of lithium ion battery is much bigger from the one of lead acid. This is a combination of sizing and general cost of this technology.

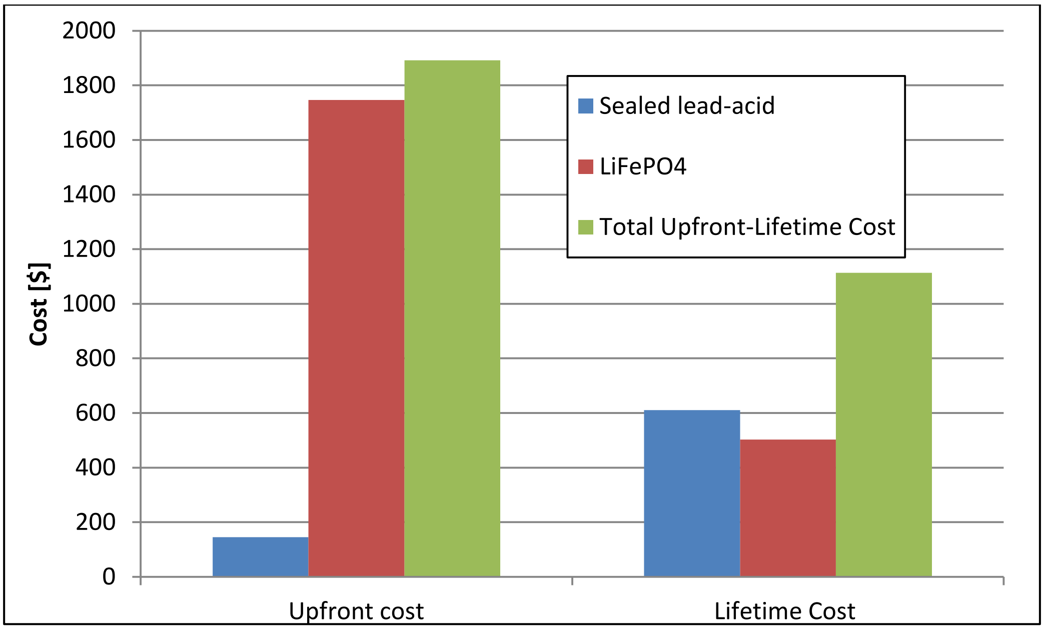


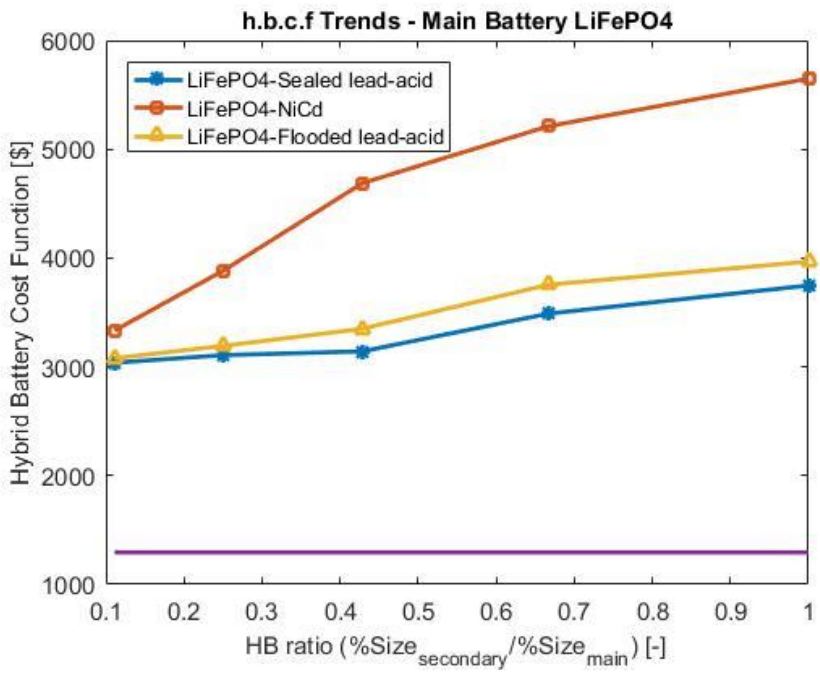
Figure 6-22: Lifetime and Upfront cost for the best Case Scenario in PM A - Case study 2

6.8.2. For Power Management B (PM B)

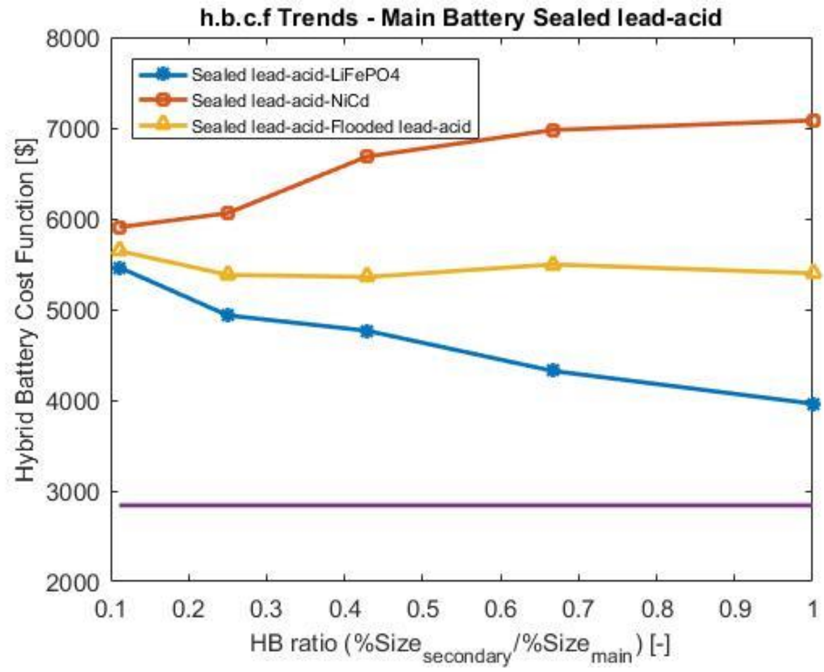
6.8.2.1. Case study 1

The results for the hybrid battery cost function for power management B (C-rate control) when varying the sizing percentage from 50 to 90 Wh, for all different battery technology combinations, are shown In Table 28 in the Appendix for Case study 1.

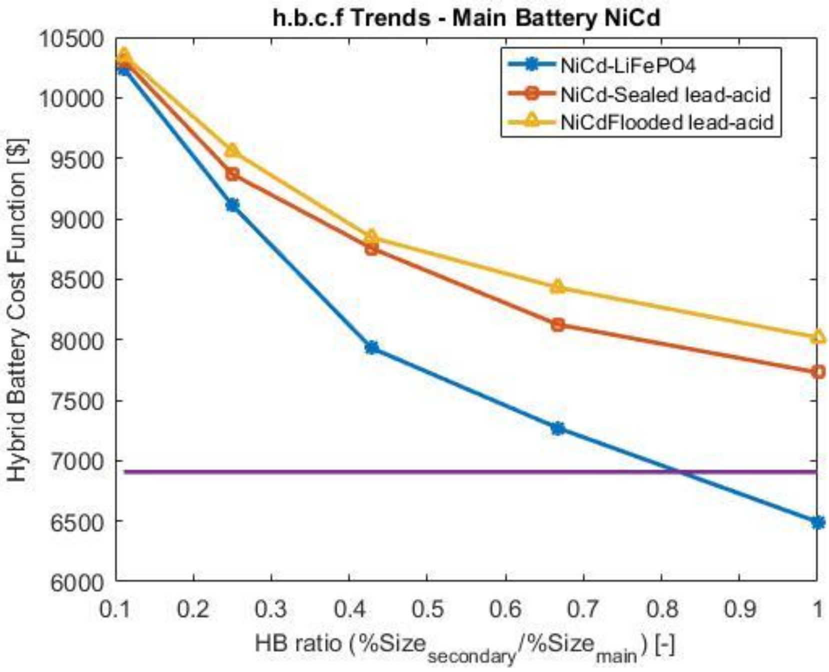
The general trends that were followed from the Hybrid battery cost function calculation can be shown in Figure 6-23 for each one of the battery combination cases, grouped together in figures with the same main battery technology.



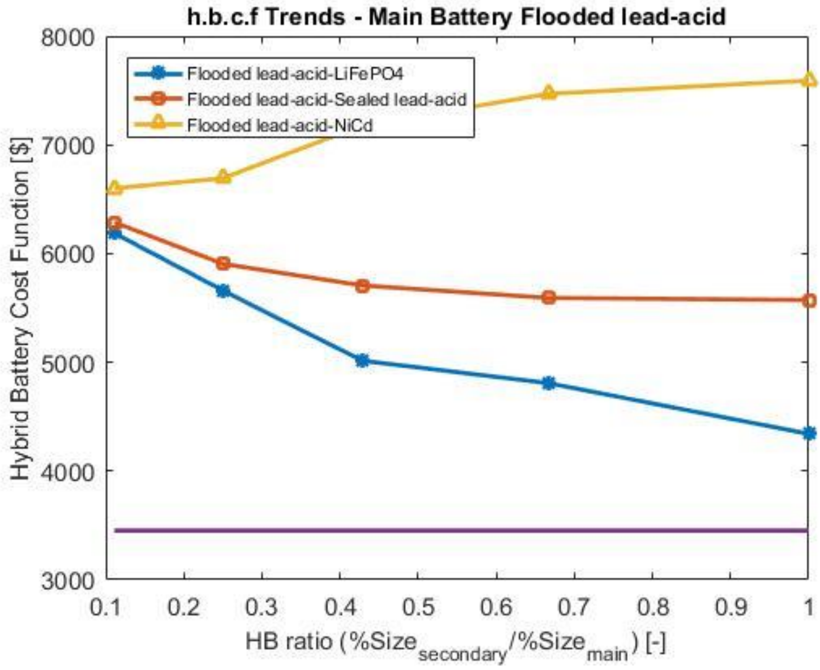
(a)


h.b.c.f Trends - Main Battery Sealed lead-acid
Sealed lead-acid-LiFePO4
Sealed lead-acid-NiCd
Sealed lead-acid-Flooded lead-acid
Hybrid Battery Cost Function [$]
HB ratio (%Size secondary/%Size main) [-]

(b)


h.b.c.f Trends - Main Battery NiCd
NiCd-LiFePO4
NiCd-Sealed lead-acid
NiCdFlooded lead-acid
Hybrid Battery Cost Function [$]
HB ratio (%Size secondary/%Size main) [-]

(c)



(d)

Figure 6-23: Hybrid Battery cost function trends for different battery technology combinations, for PM B-Case Study 1. (a) -main battery LiFePO4, (b)-main battery Sealed lead-acid, (c)-main battery NiCd, (d)- main battery Flooded lead-acid. Purple line represents the b.c.f for 100% of the Individual main technology

Observations from h.b.c.f trends

- Observing the h.b.c.f trends shown in Figure 6-23 for PM B many observations can be made. The most important observation is that using this Power management is much more expensive almost in all cases, than using 100% of one battery technology. The only exception is when NiCd battery is mixed with LiFePO4 technology for a sizing ratio equal to 50-50% (HB ratio=1). Thus the main conclusion is that it is better to use PMA in order to reach better h.b.c.f results.

- Another trend that is shown clearly has to do with the combinations that include NiCd battery technology. When this technology is used as the secondary battery, as its size is increased - decreasing the size of the main technology, the h.b.c.f shows an upward trend, showing that the lifetime costs of the hybrid battery system are increasing. As NiCd was considered the cheapest technology, the increasing lifetime cost of the configuration shows that its replacements are increasing. The fact that this technology is the worst in terms of cost and lifetime is also shown Figure 6-23 (c) where NiCd represents the main technology of the configuration. As it is blended with the other technologies, the h.b.c.f decreases for all cases.

- Another observation Is that when both of the lead acid batteries are used as the main technology, their h.b.c.f presents a downward trend as they becoming smaller and their secondary technology size is increasing especially when they are combined with lithium-ion technology. However when the secondary technology is the Nickel-based battery their cost function shows to be increasing confirming even further the short lifetime of NiCd technology.

In order to analyse better PM B the best case scenarios for each main battery technology were summarized in one table and compared to the results when only one battery technology was used.

Table 22: Best Case Scenarios for all four cases using different main battery technologies, with their optimal corresponding sizing ratio and their minimum h.b.c.f value (PM B – Case Study 1).

Best Case Scenarios for Hybrid Battery Cost Function [$]				
Secondary / Main	**LiFePO4**	**VRLA**	**NiCd**	**Flooded**
LiFePO4	1.29 E+03 **[100%]**	3.04E+03 **[90%-10%]**	3.33E+03 **[90%-10%]**	3.08E+03 **[90%-10%]**
VRLA	3.96E+03 **[50%-50%]**	2.84 E+03 **[100%]**	5.91E+03 **[90%-10%]**	5.36E+03 **[70%-30%]**
NiCd	6.49E+03 **[50%-50%]**	7.73E+03 **[50%-50%]**	6.91 E+03 **[100%]**	8.02E+03 **[50%-50%]**
Flooded	4.34E+03 **[50%-50%]**	5.57E+03 **[50%-50%]**	6.60E+03 **[90%-10%]**	3.45 E+03 **[100%]**

The best Hybrid battery technology combination (excluding the cases when 100% of a single battery technology was used) is appeared to be the case when 90% of battery size is represented by LiFePO4 technology and 10% by sealed lead acid. The upfront and lifetime cost of the two battery technologies as well as the number of replacements needed are shown in Table 23.

Table 23: Optimal Storage choice for PM B and Case study 1

	LiFePO4 [main]	**Sealed lead-acid [secondary]**
Sizing ratio [%]	90	10
Size [Ah]	333	37
Number of replacements [-]	10	11
Upfront Cost [$]	561.82	46.79
Lifetime Cost [$]	2223.74	205.36
h.b.c.f [$]	3.04E+03	

It can be seen that using PM B both of the battery technologies need almost equal amount of replacements, 10 and 11.This can be explained by the fact that the main battery technology, in this case LiFePO4 is used almost constantly and even though it is not undergoing deep charges and discharges as it handles the average loads, it is still used a lot more that the secondary battery technology which is sealed lead acid. In addition, lead acid battery exhibits even lower lifetime as it undergoes deep charging discharging cycles for the satisfaction of the peaks of the load.

The upfront and lifetime costs of the best hybrid battery choice for Case Study 1 using PM B are shown in the histogram illustrated in Figure 6-24.

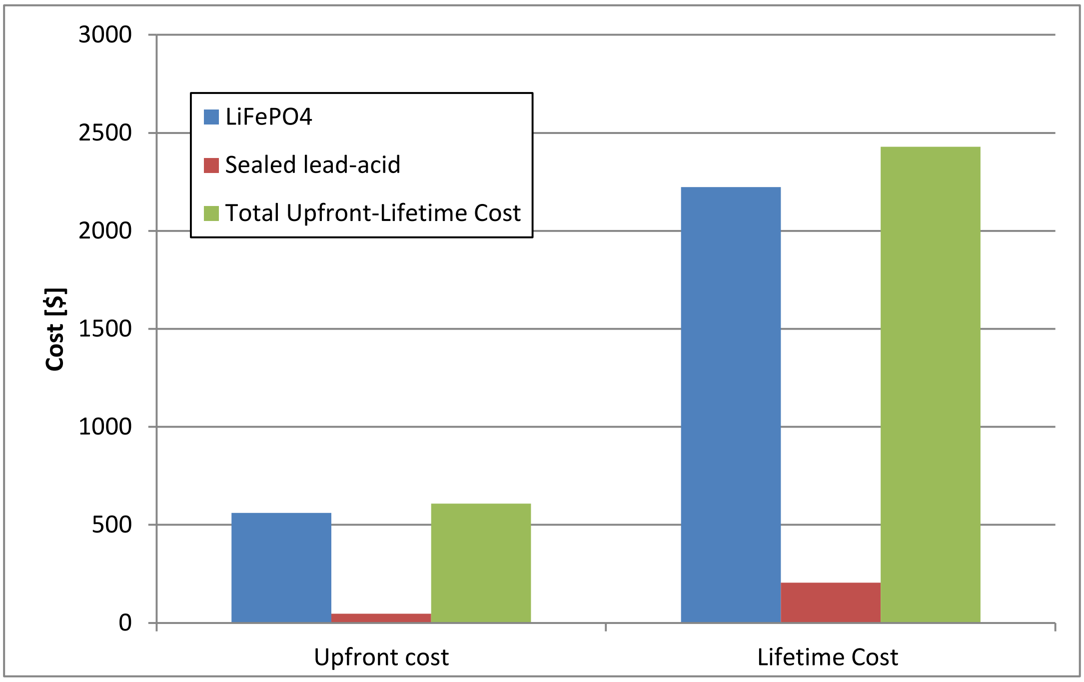


Figure 6-24: Lifetime and Upfront cost for the best Case Scenario in PM B - Case study 1

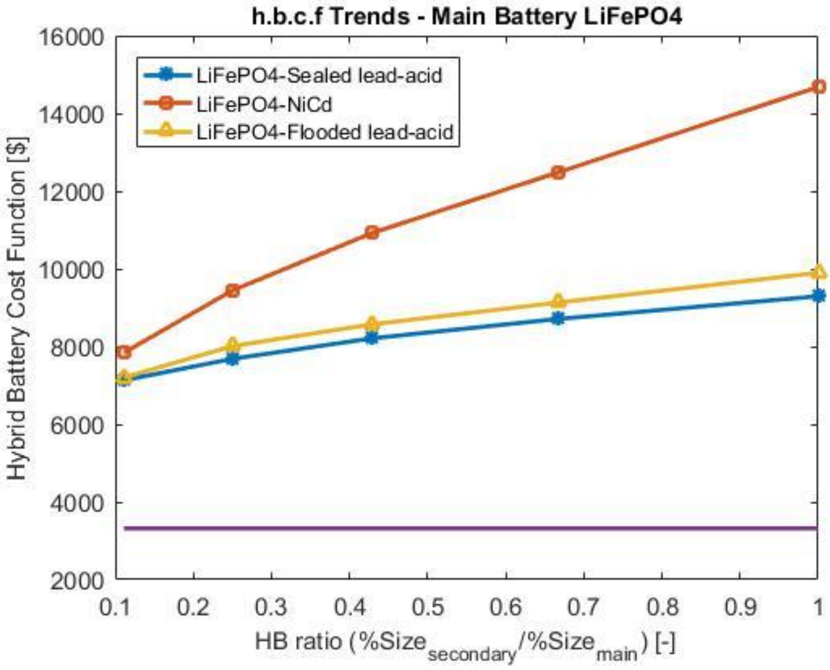
It is clear that the lifetime cost especially of LiFePO4 technology is the one that is increasing the overall cost and the h.b.c.f of the configuration as both of the technologies used required a large amount of replacements.

It is worth pointing out that even though it is obvious that PM B is not profitable at all, it was still analysed in terms of best case scenarios and different costs, in order to examine whether there is a trend followed by the battery technology combinations and best case scenarios for the different case studies. In addition it will help us to reach to conclusions about the battery usage and cycling.

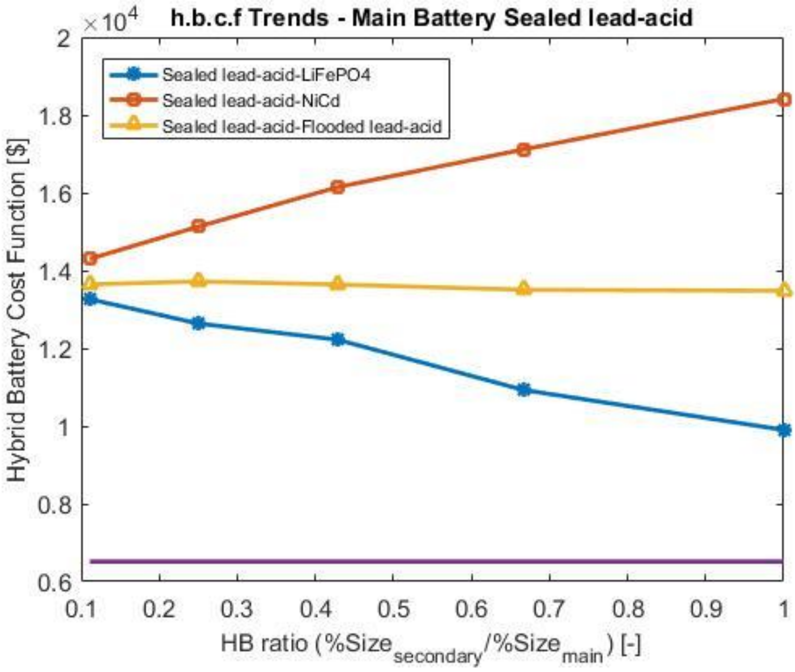
6.8.2.2. Case Study 2

The results for the hybrid battery cost function power management when varying the battery sizing percentage from 50 to 90 with a step of 10 Wh, for all different battery technology combinations, are shown at Table 29 of the Appendix A for Case study 2.

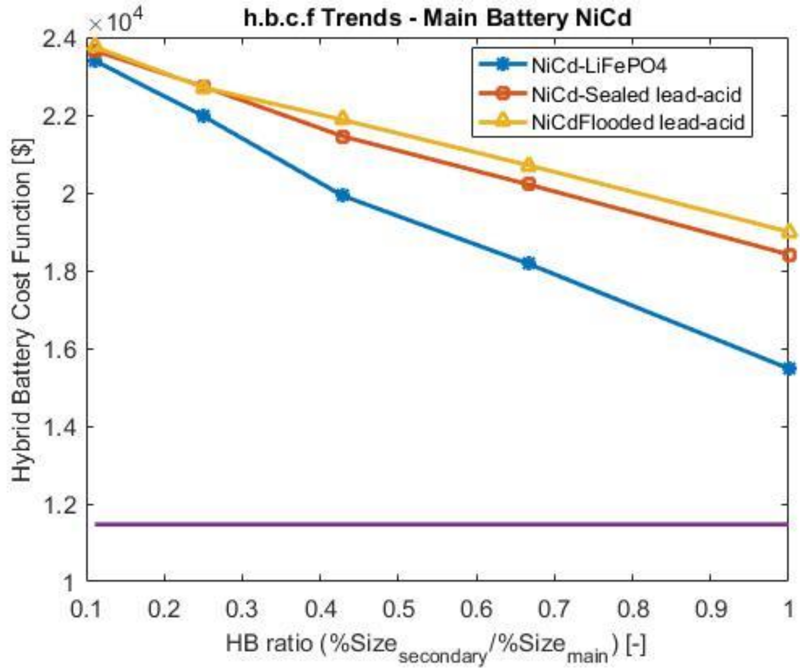
The general trends that were followed from the Hybrid battery cost function calculation can be shown in Figure 6-25 for each one of the battery combination cases, grouped together in figures with the same main battery technology.


h.b.c.f Trends - Main Battery LiFePO4
LiFePO4-Sealed lead-acid
LiFePO4-NiCd
LiFePO4-Flooded lead-acid
Hybrid Battery Cost Function [$]
16000
14000
12000
10000
8000
6000
4000
2000
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
HB ratio (%Size$_{secondary}$/%Size$_{main}$) [-]

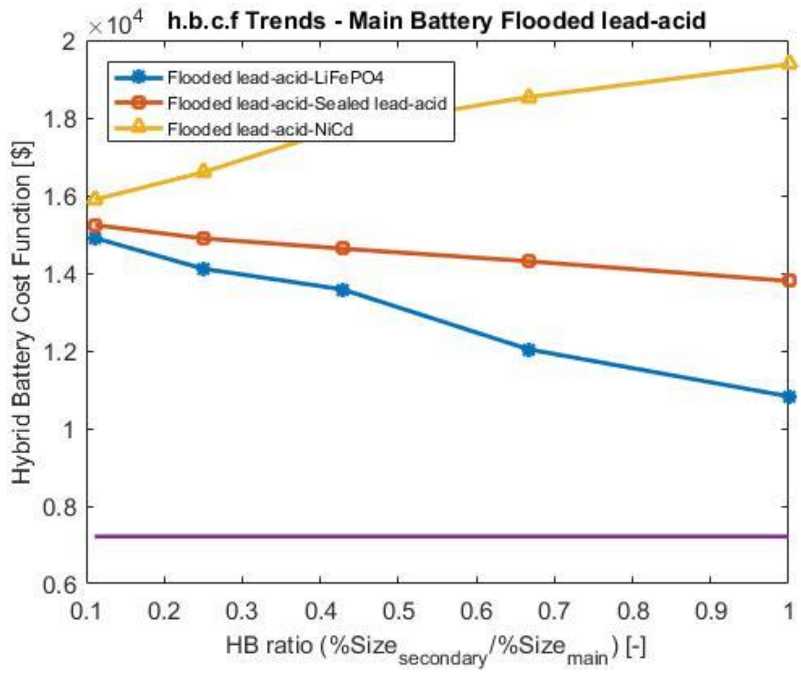
(a)


h.b.c.f Trends - Main Battery Sealed lead-acid
$\times 10^4$
Sealed lead-acid-LiFePO4
Sealed lead-acid-NiCd
Sealed lead-acid-Flooded lead-acid
Hybrid Battery Cost Function [$]
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
HB ratio (%Size$_{secondary}$/%Size$_{main}$) [-]

(b)



(c)



(d)

Figure 6-25: Hybrid Battery cost function trends for different battery technology combinations, for PM B-Case Study 2. (a) -main battery LiFePO4, (b)-main battery Sealed lead-acid, (c)-main battery NiCd, (d)- main battery Flooded lead-acid. . Purple line represents the b.c.f for 100% of the Individual main technology.

Observations from h.b.c.f trends

- Observing Figure 6-25 it is clear that it is much more expensive to choose a hybrid battery technology combination than just using one battery technology to handle all the loads. It is important to state that when using PM B the trends followed by the h.b.c.f for all the HB configurations in Case study 2 are the same as the ones followed in Case Study 1. More specifically, NiCd technology again shows to have much shorter lifetime than the other technologies. In addition, the high cost of lithium ion technology when used as the main battery in the power management scheme cannot be compensated by its high lifetime leading to a very increased value of the h.b.c.f. The best scenario h.b.c.f results of each case as well as the individual b.c.f results are shown in Table 24.

Table 24: Best Case Scenarios for all four cases using different main battery technologies, with their optimal corresponding sizing ratio and their minimum h.b.c.f value (PM B – Case Study 2).

Best Case Scenarios for Hybrid Battery Cost Function [$]				
Secondary / Main	LiFePO4	VRLA	NiCd	Flooded
LiFePO4	3.32e+03 **[100%]**	7.13E+03 **[90%-10%]**	7.84E+03 **[90%-10%]**	7.20E+03 **[90%-10%]**
VRLA	9.90E+03 **[50%-50%]**	6.52e+03 **[100%]**	1.43E+04 **[90%-10%]**	1.35E+04 **[50%-50%]**
NiCd	1.55E+04 **[50%-50%]**	1.84E+04 **[50%-50%]**	1.15 E+04 **[100%]**	1.90E+04 **[50%-50%]**
Flooded	1.08E+04 **[50%-50%]**	1.38E+04 **[50%-50%]**	1.59E+04 **[90%-10%]**	7.22e+03 **[100%]**

It can again be seen that the best case scenario is to use only LiFePO4 battery technology which minimizes the cost function. In addition, comparing these results with the ones of PM A it is better to use hybrid battery configurations determined there. Excluding the single battery technology results, the best hybrid configuration of PM B is the one with 90% of the battery size using LiFePO4 and 10% of sealed lead acid. More details about this hybrid battery configuration are shown in Table 25.

Table 25: Optimal Storage choice for PM B and Case study 2

	LiFePO4 [main]	Sealed lead-acid [secondary]
Sizing ratio [%]	90	10
Size [Ah]	1035	115
Number of replacements [-]	7	7
Upfront Cost [$]	1.75e+03	1.45e+02
Lifetime Cost [$]	4.85e+03	3.86e+02
h.b.c.f [$]	7.13E+03	

I can again be seen that the cost that increases the overall h.b.c.f is the lifetime cost of the batteries as they both need seven replacements throughout the overall 25 year system lifetime. This can be better illustrated in Figure 6-26.

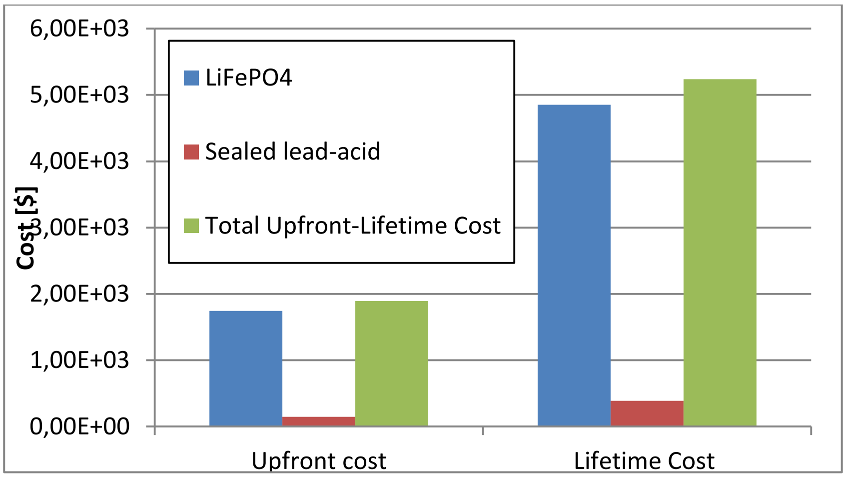


Figure 6-26: Lifetime and Upfront cost for the best Case Scenario in PM B - Case Study 2

6.8.3. Battery Sizing and Hybrid Battery Cost Function Trade-offs

In order to examine whether oversizing the battery could lead to more satisfactory results, meaning smaller h.b.c.f thus, higher battery lifetime and less number of replacements the simulation was run for a variation of different battery sizes. The oversizing of the battery was applied to the best case scenarios of every case study and power management.

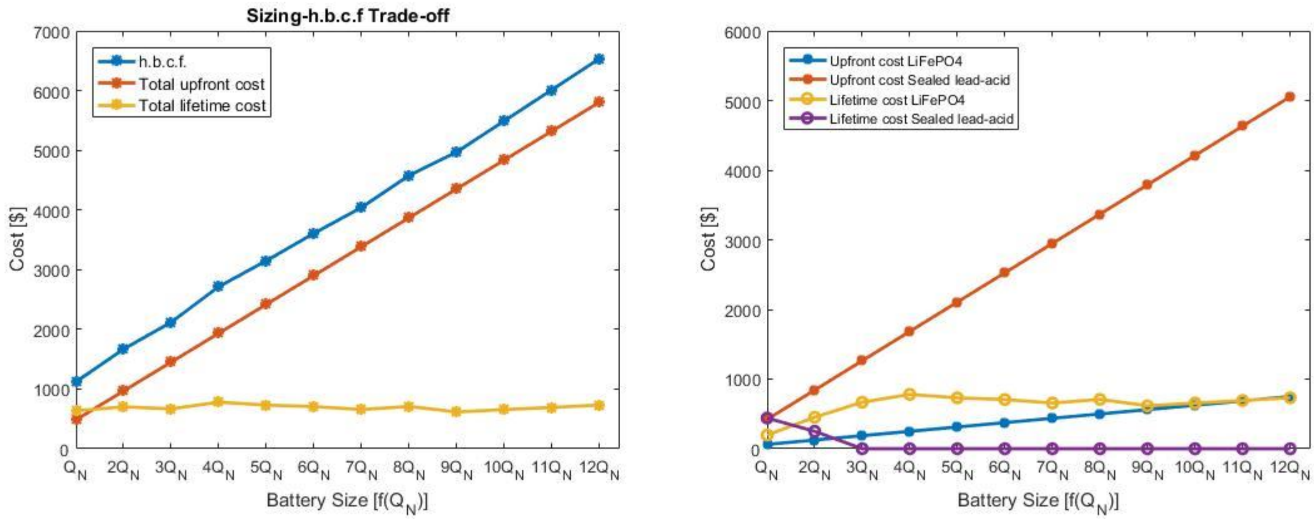
Power Management A

For power management A the results of the h.b.c.f trade-offs with the size of the battery are shown in Figure 6-27 and Figure 6-28 for Case studies 1 and 2, respectively. The figures on the left include the total upfront and lifetime cost of the configuration as well as the h.b.c.f curve, while the figures on the right compare the upfront and lifetime cost of the two different batteries that are part of the HB.

As it can be seen from Figure 6-27 (a) and Figure 6-28 (a), for both case studies the h.b.c.f keeps increasing as the battery is oversized. The upfront cost of the total configuration naturally keeps increasing linearly while the battery size increases, as they are proportional. This can also be justified from Figure 6-27 (b) and Figure 6-28 (b) where the upfront costs of both battery technologies that form the hybrid configuration increase linearly with the battery capacity increase.

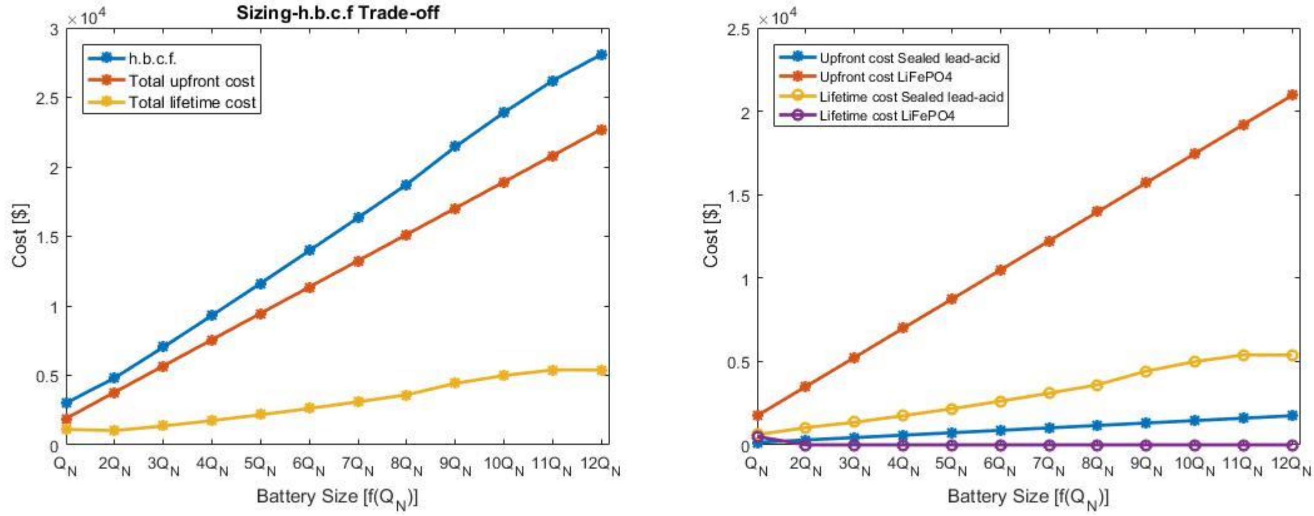
The lifetime costs on the other hand, are more complex to explain. Starting from Case Study 1, it is seen that the total lifetime cost is almost kept constant as the battery capacity increases. As it can be seen from Figure 6-27 (b) the lifetime cost of the secondary battery technology, in this case Sealed lead-acid becomes zero when the battery is oversized by 3 and stays zero until the end. Thus, this battery technology undergoing the cycling of the specific load profile and used as secondary battery in PM A is able to last 25 years. The main battery on the other hand, exhibits increasing lifetime costs at the beginning but after oversizing the battery by 4 times its lifetime costs are shown to be decreasing. This is happening because the battery is able to last more as it is oversized leading to less number of replacements.

Something very similar to Case Study 1 is happening at the second case study trade-off curves. The total lifetime cost of the hybrid configuration equals to the sealed-lead acid lifetime cost after oversizing the battery by 2. This is when the secondary battery (LiFePO4) does not need any replacements having only upfront cost. Again the h.b.c.f continues increasing when oversizing the battery due to battery usage and activity at the specific application.



(a) (b)

Figure 6-27: (a) Hybrid Battery cost function (b.c.f.) and sizing trade-off for PM A - Case Study 1 and (b) Different battery cost trade-offs.



(a) (b)

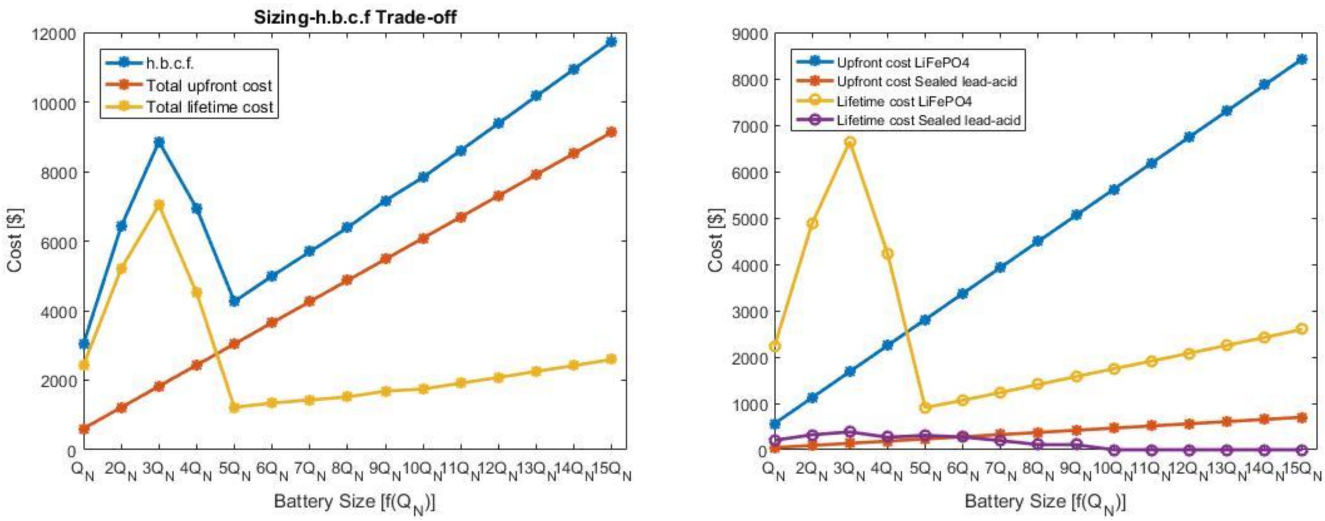
Figure 6-28: (a) Hybrid Battery cost function (b.c.f.) and sizing trade-off for PM A - Case Study 2 and (b) Different battery cost trade-offs.

Power Management B

For power management B, Case study 1 we can observe big fluctuations in the h.b.c.f but still not enough to become smaller than the value that the function when the battery is not oversized. For Case study 1 as it is again logical the upfront costs of the batteries as well as the total upfront cost keep increasing linearly with size. The lifetime cost of the configuration on the other hand, shows a very steep decrease when oversizing the battery by 4 and 5 times and then it continues increasing gradually. Observing Figure 6-29 (b) the big fluctuation happens in the lifetime of the main battery LiFePO4. As the battery capacity is oversized up to 3 times the number of replacements needed for this technology, are 10, 11 and then 10 again. The increase in the number of replacements as the battery is oversized from Q_N to $2Q_N$ has to do with the active time periods of the battery. This is happening because as the battery sizing increases, the systems fails less to satisfy the load, thus the battery lies empty or full less time periods resulting to more cycling. As the battery cycles more the number of these cycles are the ones that count until the EOL as the EOL cycle number in this lifetime model is predetermined by the manufacturer datasheets. Thus higher amount of cycles leads to shorter lifetime of the battery. This phenomenon can be justified as the calculation of the battery size for LLP equal to 0.4% takes into account a battery efficiency of 95% while here the battery efficiency is smaller.

After oversizing the battery by 4 and 5 times the lifetime of the battery increases significantly as it requires 5 and 1 replacements, respectively (thus the lifetime cost decreases). After that, the lifetime of the battery continues increasing but still needs one replacement as it never reaches 25 years of lifetime. Thus, the lifetime cost of the battery becomes proportional to the battery size and not to the replacements from 5 to 15 times the battery size.

Observing the lifetime of the secondary technology on the other hand (sealed lead-acid) is seen that it becomes zero after oversizing the battery by 10 as the main battery is almost able to handle all of the load individually even when the secondary battery fails to handle the peaks. The replacements of the battery decrease gradually as the battery capacity is oversized. The replacement curves with the battery oversizing are shown in Appendix A.

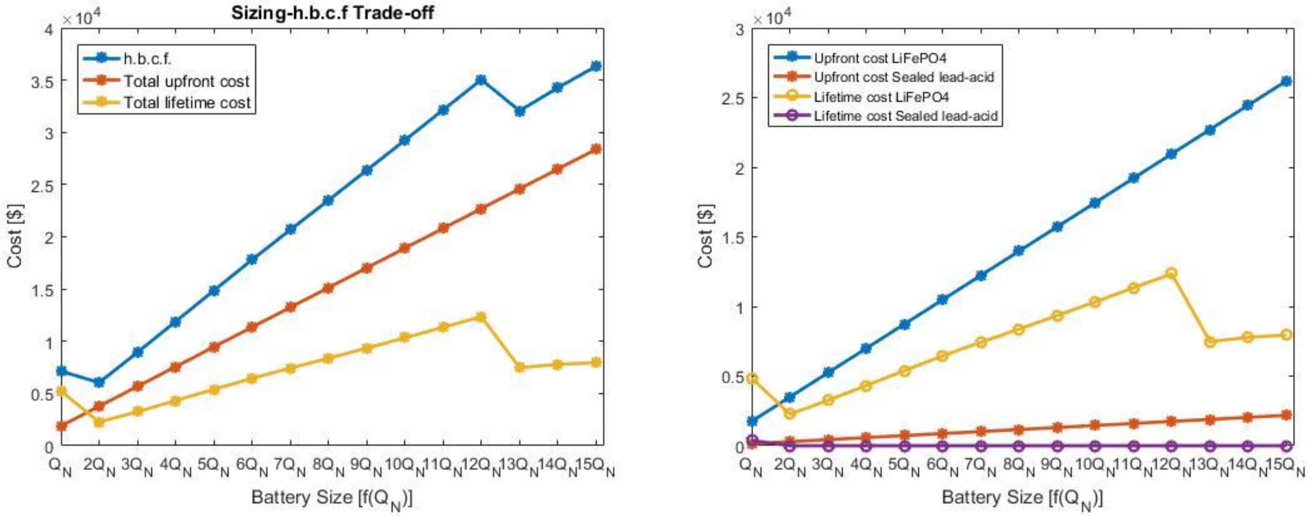


(a) (b)

Figure 6-29: (a) Hybrid Battery cost function (b.c.f.) and sizing trade-off for PM B-Case Study 1 and (b) Different battery cost trade-offs.

For the second case study, it can again be seen that the overall h.b.c.f almost equals to the combination of the upfront and lifetime costs of the main technology (LiFePO4) as it possess 90% of the total hybrid battery size. Some fluctuations can again be seen in the lifetime of the main battery technology, when the lifetime increases significantly from one point to another in a degree that is able to decrease the lifetime cost of the battery. It is important to see that when oversizing the hybrid battery by 2 times the h.b.c.f becomes a little bit smaller than the value it had before oversizing the battery. In this case the replacements of the main battery drop from 7 to 2 as the lifetime increases from 3 to 10 years while the size is only doubled, something that is not enough to increase the cost that much. This is also happening because the secondary battery needs zero number of replacements when oversizing the battery by any number. In addition after reaching 13 times the battery size the replacements of the main battery become one per year, thus the sudden drop in the lifetime cost too. The replacement curves with the battery size are again shown in Appendix A.

Having all of the above in mind, it is clear that the trade-off between cost, sizing and lifetime are very depended to the specific cycling and usage that the battery undergoes for a specific application, load profile and power management.



(a) (b)

Figure 6-30: (a) Hybrid Battery cost function (b.c.f.) and sizing trade-off for PM B - Case Study 2 and (b) Different battery cost trade-offs.

6.9. Conclusions

The main conclusion of this chapter is that indeed there is a hybrid battery configuration that is able to decrease the battery cost function becoming smaller than the value it has when only using one individual battery technology. Different hybrid battery configurations were decided to be the optimum ones for the different sets of PV-load case studies that were examined. The final best case scenarios of Power Management A and B compared to the individual technologies taking part in the HB configuration are summarized in Figure 6-31. The two arrows point out the cases when cost function is minimized for both case studies. It is seen that keeping things simple with Power Management A has led to the best cost function values resulting to the optimum HB battery choices for Case studies 1 and 2.

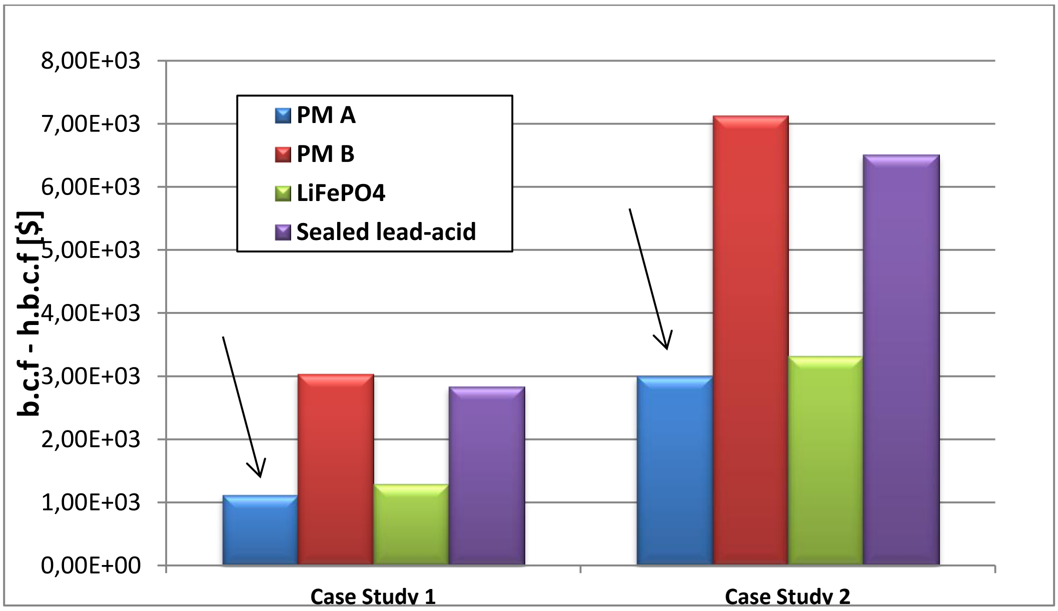


Figure 6-31: Best case scenarios as obtained from all of the results

The technologies that take part in the optimum hybrid battery configurations for both case studies are lithium ion, more specifically lithium iron phosphate and sealed lead-acid. These batteries exhibit the best combination of cost and lifetime in order to represent the most suitable storage technology to be used at Solar Home System applications. While lithium ion battery has the higher lifetime of all technologies by far, its high cost is making it competitive with the lead acid technology. Even though lead-acid has much shorter lifetime the low cost of the technology is decreasing the overall cost of Hybrid battery cost function.

Taking into consideration that the costs of Lithium ion batteries are going to be decreased significantly in the future it could also be said that another option, is using hybrid battery configuration at the beginning of the System lifetime and after it fails replacing it with only lithium ion technology if its price is indeed a lot decreased by the time that the configuration needs replacement. As it can be seen from Figure 6-31 the cost difference between the optimal HB configuration for both Case studies 1 and 2, and the choice of using a single technology of LiFePO4, is very small, accounting to almost 13% and 10% respectively. Thus it could indeed be an option to replace the HB configuration with only lithium ion technology after the first time that the configuration fails. For Case study 1 it could be after six years of operation as LiFePO4 battery would need only one replacement and sealed lead-acid zero. For case study 2 this could happen after the first or second time that Sealed lead-acid battery fails, as lithium ion technology there lasts for 15 years. On the other hand, there is an uncertainty on whether the price of this battery technology will actually have this dramatic decreased, as it was discussed and shown in the sensitivity analysis that was held in section 6.7 of this Chapter.

One important conclusion is that the battery lifetime and the fluctuation of the h.b.c.f is very depended on the battery usage that the technology might be undergoing under different power managements and load profiles. The way that the battery sizing methodology in combination with the lifetime prediction model was constructed allows the battery to undergo more cycling when its size is bigger up to a point mainly because efficiency of the battery used for the sizing methodology was very optimistic. This is evident by the fact that there are no clear trends followed by the best case scenarios in the two different Power managements constructed except for the technology combination that has the best results (LiFePO4 and Sealed lead-acid).

After considering all of the results, it is seen that for the cases used in this study HB configurations indeed optimize the value of the cost function but the difference of using only lithium ion battery is small and could be compensated by the additional costs that will occur for the development of the HB configuration. The installation of HB would probably require extra R&D costs as more complex Power management schemes need to be used for the power in such system.

Chapter 7

Conclusions and Future Recommendations

7.1. Thesis Retrospection

In this project four different battery technologies were examined, compared and combined together to be able to reach the best storage option for the application of Solar Home Systems. This study involved modelling of the sizing and the behaviour of different technologies, as well as of Hybrid battery technologies. A non-empirical lifetime estimation method for the batteries was proposed and combined with a cost function that was constructed for comparing different hybrid battery storage options. Finally, the optimal storage for different load cases was found.

7.1.1. Answers to the research Questions

The main objective of this project was to examine and propose the optimal storage option whether it consist of an individual battery technology or a combination of two technologies together (Hybrid battery), for the application of the Solar Home Systems. In order to do that, some other questions needed to be answered first.

- ***What is the Optimal Storage Size for different Load Scenarios taking place in a specified location?***

The first step needed to be taken, was the sizing of the system for both of the Load scenarios that were used. For the sizing of the system two different Power management Architectures were examined and compared in terms of the battery size based on LLP minimization and the energy throughput minimization. After considering the results of each one of the Architectures it was concluded that Architecture 1 required smaller storage size for both load scenarios and the battery was undergoing much less cycling. The optimal sizing results for both Load case studies were obtained taking into account Architecture 1, which was also used moving forward to the methodology. For Case study 1 the optimal battery size was concluded to be 370 Wh and for case study 2 1150 Wh,

- ***How to accurately estimate the lifetime of a battery taking into account as many battery parameters and behaviours as possible for different battery technologies?***

In order to be able to take an informed and accurate decision for the optimum storage option needed, the lifetime of each battery technology had to be considered. Thus, a non-empirical lifetime estimation method is being proposed using dynamic battery capacity fading. This method started taking as a base idea, the overall lifetime zero crossings estimation method, which introduces the definition of active DOD. The many different layers of complexities were added trying to take into account as many battery parameters as possible and their contribution to battery lifetime. Including different battery efficiencies, temperature and DOD effects, active and inactive battery periods as well as cycle counting algorithm (rainflow) and a fatigue measurement rule, the dynamic model for capacity fading was constructed. The result of this proposed model is the predicted lifetime of a battery technology when being cycled for specific load profiles. It was made sure that this lifetime estimation method satisfies all of the criteria that these kind of methods need to have overcoming many challenges. The lifetime method was validated and concluded to be very realistic but a bit pessimistic.

- ***How can the upfront and lifetime costs be combined into a singular cost function while capturing the future cost trends of the different technologies?***

The next step, after being able to estimate the battery lifetime, is to have an accurate measurement of comparison between the different tested battery technologies, individual and hybrid. This measure has to include the upfront cost of the battery which is directly proportional to the battery size, as well as the lifetime cost of the battery which is proportional to battery size again, but also it need to take into account factors such as battery lifetime (with all the parameters affecting it), number of battery replacements needed during the lifetime of the Solar Home System and future battery costs accounted for their replacement. Taking all of the above into consideration a battery cost function (b.c.f) for the individual technologies and a hybrid battery cost function (h.b.c.f) of the Hybrid battery system were constructed. The future battery cost trends were approximated using cost learning for the different technologies and incorporated into the overall battery cost function used for the calculation of the lifetime cost.

- ***What are the limitations of individual battery technologies? How can the hybrid battery combine the best features of each technology?***

After comparing lifetime results of all the individual technologies used in this chapter in many stages of the chapter some general conclusions for the technologies were drawn. First, the technology that exhibits higher tolerance in cycling in the application of Solar Home Systems is the lithium ion technology as it appears to have longer lifetime of all the other technologies needed less number of replacements throughout the whole system lifetime. Sealed lead acid batteries experience less battery lifetime but still could be used in such applications while NiCd batteries experience the smallest efficiency and shortest lifetime of all technologies. The trade-off between battery lifetime and technology selection has to do with the battery cost. Lithium ion batteries are the most expensive technologies showing downward trends while nickel cadmium batteries are the most cheap remaining more or less constant. Lead acid on the other hand also experience a downward cost trend but is a lesser extent than lithium ion.

The optimal hybrid battery calculated in chapter 6 was able to combine the best features of the two technologies combined in terms of lifetime and cost being able to minimize the cost function.

- ***Which optimal Battery Technology or Hybrid Battery configuration can optimize the storage Cost function for a given set of PV-Load profile?***

  The Hybrid battery configuration that was found to optimize the hybrid battery cost function was different for the different case studies. For Case study 1 (low LP) the optimum storage configuration was found to be consisted of 10% of the total storage size by LiFePO4 technology and 90 % of the total storage size by Sealed lead-acid, cycling with Power management A. For Case study 2 (medium LP) the optimum configuration consists of 10 % Sealed lead acid battery and 90% LiFePO4 cycling with power management A.

7.1.2. **General Conclusions**

- One of the most important conclusions that were drawn from the project is that battery lifetime is very dependent on the active and inactive periods that it has during its operation, thus very dependent on the specific battery usage, load profile that is used. This was very evident in times that the battery sizing was varied resulting to different battery cycling. Thus, different results are expected for battery lifetime if the same technology is used in different application.

- In terms of lifetime modelling it is very important to point out that the general methodology constructed can be applied to any type of battery technology and brand as long as the manufacturer lifecycle curves can be found or constructed accurately. The lifetime model was able to combine the different technology aging characteristic together leading to a very satisfying result.

- In terms of battery and lifetime modelling it very important to point out that the model constructed purely sticks to energy balance through the overall SHS. The battery was examined in a system-level approach as a black box, and its behaviour was modelled by adding the manufacturer's datasheet curves. Thus all the models constructed had to do with power managements and power flow schemes inside the overall System and it is not an electrical model.

- In terms of the battery cost function, the result is very depended on future battery cost forecasts. Thus after the sensitivity analysis was carried it was seen that the b.c.f result can easily be changed a lot when experiencing a small change in the cost trends.

- The calendar life of the battery was not included in this study. As mentioned in the literature review, the battery technology that experiences the higher calendar life degradation is lithium ion. Thus, it is conjectured to the best of author's knowledge, that if calendar fading is applied in all of the technologies it is expected for lithium ion technology to have smaller lifetime differences especially with lead acid batteries.

- The most important conclusion that can be drawn from this study is that a battery is a very complex component that can behave a lot differently when the ambient or operating conditions change. This was very evident in the results, as a general trend for everything was not able to found. More specifically, even though the best case scenarios in both case studies include LiFePO4 and Sealed lead-acid technology, the HB ratio was different in each case as well as the main and secondary technology used.

- If more accurate datasheet information were used, for temperature cycle life curves, then the results could also be more accurate in terms of the optimal storage configuration decided.

7.2. Recommendations and Future Work

One of the main challenges that this project had to face was the need to be able to obtain the same data and curves for four different battery technologies, so that they could be compared properly. Due to limited manufacturer data, some assumptions and simplifications needed to be made. More specifically:

- A more accurate sizing methodology could be followed, including dynamic battery and converter efficiencies with the change of the power of the system. This would have led to a more accurate battery size for the load cases examined minimizing the LLP (system failure to satisfy the load measurement). In addition different efficiencies for different battery technologies could be used. Lastly, the dynamic capacity fading could also be included into the sizing methodology as well as the temperature effects.

- In the dynamic capacity fading code, calendar fading could also be added for the different technologies, in order to make the lifetime prediction of the battery even more accurate. The calendar fading methodology proposed in this study was concluded to be highly pessimistic as it accounts for every inactive period of the battery in the aging process while not considering battery relaxation periods. In order to be used more accurately it could be applied to the battery after a year of operation accounting all the inactive periods and an average temperature. This model would have been more realistic but also not very accurate.

- The efficiency of the battery was considered to be constant as the battery undergoes aging and fades when the dynamic capacity fading model is applied. In real time applications this is not the case as the efficiency of the battery should also be reduced as the battery is operating through the years. A future recommendation is to also reduce the efficiency of the battery dynamically as the battery degrades.

- As this methodology is applied to Solar Home Systems that represent low power applications with very slow charging and discharging rates, the C-rate effect was not included. In the future if this model has to be used in application with smaller C-rates there is going to be a deviation in the final results as they will appear to be more optimistic. As the C-rate increases, the temperature increases; thus the battery lifetime decreases. One future improvement could be to include C-rate or C-rate deviations in order to be able to apply the method in a wider range of applications.

- In order for even more accurate results to occur from the two cost function calculated, the cost factor curves can be normalized into the specific years' currency value taking into account inflation etc.

- In the future a multi-objective optimization could take place optimizing all of the aspects and layers that were taken into account in this model such as considering different level of LLP optimization and battery sizing for all the different load cases as well as battery technologies and configurations. Different battery technologies would require different battery sizing or different power management architectures. Different hybrid battery configurations would also require the same. By optimizing and customizing every level of the procedure followed into the specific cases different and more accurate and informed result would occur.

Bibliography

[1] International Energy Agency, “ENERGY POVERTY How to make modern energy access universal?,” in *World Energy Outlook 2010*, Paris, IEA PUBLICATIONS, 2010, pp. 237-269.

[2] N. Narayan, T. Papakosta, V. Vega-Garita, J. Popovic-Gerber, P. Bauer and M. Zeman, “A simple methodology for assessing battery lifetimes in Solar Home System Design,” Cape Town, 2017 [unpublished].

[3] U. B. Akuru, I. E. Onukwube, O. I. Okoro and E. S. Obe, “Towards 100% renewable energy in Nigeria,” *Renewable and Sustainable Energy Reviews,* vol. 71, pp. 943-953, 2016.

[4] A. I. Lacayo, “Off-grid Energy in Rural India: Policy Recommendations for Effective UN Projects,” *WWS Undergraduate Task Force: Energy for Sustainable Development,* 2006.

[5] R. Howell, *Harnessing SolarPower for Productive Use,* Delft: Delft University of Technology, 2014 [thesis project-upublished].

[6] Global LEAP, “Clean energy ministerial-The State of the off-grid appliance market,” 29 February 2016. [Online]. Available: http://www.cleanenergyministerial.org/. [Accessed 10 December 2016].

[7] H. Joern, V. Jonas, T. S.Schmidt and VolkerH.Hoffmann, “The economic viability of battery storage for residential solar photovoltaic systems – A review and a simulation model,” *Renewable and Sustainable Energy Reviews,* vol. 39, pp. 1101-1118, 2014.

[8] F. Nieuwenhout, A. Dijk, P.E.Lasschuit, G. Roekel, V. v. Dijk, D.Hirsch, H. Arriaza, M. Hankins, B. D. Sharma and H. Wade, “Experience with Solar Home Systems in Developing Countries: A Review,” *Progressing in Photovoltaics: Research and Applications,* vol. 9, no. 6, pp. 455-474, 2001.

[9] A. Greg, E. Jake and A.-H. Said, “A Comparison of Lead Acid to Lithium-ion in Stationary Storage Applications,” AllCell Technologies LLC, 2012.

[10] J. O. GilPosada, A. J.R.Rennie, S. P. Villar, V. L.Martins, JordanMarinaccio, AlistairBarnes, C. F.Glover, D. A.Worsley and P. J.Hall, “Aqueous batteries as grid scale energy storage solutions,” *Renewable and Sustainable Energy Reviews,* vol. 68, pp. 1174-1182, 2017.

[11] Battery University, “BU-205: Types of Lithium-ion,” 28 June 2017. [Online]. Available: http://batteryuniversity.com/learn/article/types_of_lithium_ion. [Accessed 3 July 2017].

[12] M. Root, The Tab Battery Book: An in- Depth Quide to Construction, Design and Use, Mc Graw Hill, 2010.

[13] T. JM. and A. M., “Issues and challenges facing rechargeable lithium batteries,” *Nature,* vol. 414, pp. 359-67, 2001.

[14] B. H.J. and W. K. P. Notten, “Electronic-network modelling of rechargeable NiCd cells and its application to the design of battery management systems,” *Journal of Power Sources,* vol. 77, pp. 143-158, 1999.

[15] ElectraBattery, “LEAD ACID BATTERIES - TYPES AND CHARACTERISTICS ...,” 2014. [Online]. Available: http://electrabattery.com/en/lead-acid-batteries-types-and-characteristics.html. [Accessed 16 June 2017].

[16] O. Mehul, J. Paul and R. Zhao, *A comparative study of LFP Batteries and traditional Lithium Batteries,* California: University of Southern California, 2010.

[17] A. Green, “The characteristics of the nickel-cadmium battery for energy storage,” *Power Engineering Journal,* vol. 13, no. 3, pp. 117-121, 1999.

[18] P. Bernard and M. Lippert, “Nickel-Cadmium and Nickel-Metal Hydride Battery Energy Storage,” in *Electrochemical Energy Storage for Renewable Sources and Grid Balancing*, Amsterdam, Elsevier, 2015, pp. 223-251.

[19] epec, “NICKEL BATTERY TECHNOLOGIES,” epec: build to print electronics, 2017. [Online]. Available: http://www.epectec.com/batteries/nickel-battery-technologies.html. [Accessed 16 June 2017].

[20] “BU-1006: Cost of Mobile and Renewable Power,” Cadex, 19 May 2017. [Online]. Available:

http://batteryuniversity.com/learn/article/bu_1006_cost_of_mobile_power. [Accessed 10 June 2017].

[21] K. Divya and J. Østergaard, “Battery energy storage technology for power systems—An overview,” *Electric Power Systems Research,* vol. 79, pp. 511-520, 2009.

[22] A. H. Smets, K. Jäger, O. Isabella, R. A. v. Swaaij and M. Zeman, Solar energy: The physics and engineering of photovoltaic conversion, technologies and systems, Cambridge : UIT Cambridge Ltd, 2016.

[23] M.Ceraolo, G.Lutzemberger and D.Poli, “State-Of-Charge Evaluation Of Supercapacitors,” *Journal of Energy Storage,* vol. 11, pp. 211-218, 2017.

[24] S. D. Uwe, B. Georg, J. Andreas and J. Garche, “State of charge - What do we really speak about ?,” 1999.

[25] L. Serrao, Z. Chehab, Y. Guezennec and G. Rizzoni, “Aging Model of Ni-MH Batteries for Hybrid Electric Vehicles,” in *Vehicle Power and Propulsion, 2005 IEEE Conference*, 2005.

[26] L. Lu, X. Han, J. Li, J. Hua and M. Ouyang, “A review on the key issues for lithium-ion battery management in electric vehicles,” *Journal of Power Sources,* vol. 226, pp. 272-288, 2013.

[27] R. Spotnitz, “Simulation of capacity fadein lithium ion batteries,” *Journal of Power Sources,* vol. 113, pp. 72-80, 2003.

[28] IRENA: Internation Renewable Energy Agency, “Battery Storage for Renewables: Market Status and Technology Outlook,” IRENA: Internation Renewable Energy Agency, United Arab Emirates, 2015.

[29] M. R. Palacín and A. d. Guibert, “Why do batteries fail?,” *SCIENCE,* 5 February 2016.

[30] M.Broussely, Ph.Biensan, F.Bonhomme, Ph.Blanchard, S.Herreyre, K.Nechev and R.J.Staniewicz, “Main aging mechanisms in Li ion batteries,” *Journal Power Sources,* vol. 146, pp. 90-96, 2005.

[31] P. W. C. N. V. R. S. Matthew T. Lawder, “Model-Based SEI Layer Growth and Capacity Fade Analysis for EV and PHEV Batteries and Drive Cycles,” *Journal of The Electrochemical Society,* vol. 161, pp. A2099-A2108, 2014.

[32] P. Keil, S. F. Schuster, J. Wilhelm and A. Jossen, “Calendar Aging of Lithium-Ion Batteries I. Impact of the Graphite Anode on Capacity Fade,” *Journal of The Electrochemical Society,* vol. 163, pp. A1872-A1880, 2016.

[33] H. Al-Sheikh and N. Moubayed, “Health Status and Diagnosis of Batteries in Renewable Energy Systems: An Overview,” in *Electrical and Power Engineering (EPE), 2012 International Conference and Exposition* , Iasi, 2012.

[34] N. Narayan, J. Popovic, J.-C. Diehl, S. Silvester, P. Bauer and M. Zeman, “Developing for Developing Nations: Exploring an Affordable Solar Home System Design,” in *Global Humanitarian Technology Conference*, Seattle, 2016.

[35] Panasonic Batteries, “Valve-Regulated Lead-Acid Batteries Technical Handbook 03/04,” Panasonic Batteries, 2003.

[36] Hoppecke power from innovation, *Installation, commissioning and operating instructions for valve-regulated stationary lead-acid batteries,* vol. 1.2, HOPPECKE Batterien GmbH, 2015.

[37] Hoppecke Power from Innovaation, *Installation, commissioning and operating instruction for vented lead-acid batteries,* vol. 1.1, HOPPECKE Batterien GmbH & Co. KG, 2013.

[38] C. Simpson, “Chacteristics of Rechargeable Batteries,” Texas Instruments Incorporated, Dallas, 2011.

[39] P. T.Guena, “How Depth of Discharge Affects the Cycle Life of Lithium-Metal-Polymer Batteries,” *IEEE,* 2006.

[40] Alpha Power, *Industrial Ni-Cd Batteries Standard Range Technical Manual,* Alpha Technologies, Inc., 2009.

[41] Valence , “Long Cycle life,” Valence , [Online]. Available: https://www.valence.com/why-valence/long-lifecycle/. [Accessed 10 February 2017].

[42] Y. Wu, P. Keil, S. F. Schuster and A. Jossen, “Impact of Temperature and Discharge Rate on the Aging of a LiCoO2/LiNi0.8Co0.15Al0.05O2 Lithium-Ion Pouch Cell,” *Journal of Electrochemical Society,* vol. 164, no. 7, 2017.

[43] J. Shen, S. Dusmez and A. Khaligh, “An Advanced Electro-Thermal Cycle-Lifetime Estimation Model for

LiFePO4 Batteries," *Transportation Electrification Conference and Expo (ITEC), 2013 IEEE,* 5 August 2013.

[44] V. Marano, S. Onori, Y. Guezennec, G. Rizzoni and N. Madella, "Lithium-ion Batteries Life Estimation for Plug-in Hybrid Electric Vehicles," in *Vehicle Power and Propulsion Conference, 2009. VPPC '09. IEEE*, Dearborn, 2009.

[45] C. Zhang, K. Li, S. Mcloone and Z. Yang, "Battery Modelling Methods for Electric Vehicles - A Review," in *2014 European Control Conference (ECC)*, Strasbourg, France, 2014.

[46] "Battery Modeling for Energy-Aware System Design," *IEEE,* vol. 36, no. 12, pp. 77-87, 2003.

[47] J. Wang, J. Purewal, P. Liu, J. Hicks-Garner, S. Soukazian, E. Sherman, A. Sorenson, L. Vu, H. Tataria and M. W. Verbrugge, "Degradation of lithium ion batteries employing graphite negatives and nickel-cobalt-manganese oxide + spinel manganese oxide positives:Part 1, aging mechanisms and life estimation," *Journal of Power Sources,* pp. 937-948, 2014.

[48] J. Wang, P. Liu, J. Hicks-Garner, E. Sherman, S. Soukiazian, M. Verbrugge, H. Tataria, J. Musser and P. Finamore, "Cycle-life model for graphite-LiFePO4 cells," *Journal of Power Sources,* vol. 196, no. 8, p. 3942–3948, 2011.

[49] E. Sarasketa-Zabala, I. Gandiaga, E. Martinez-Laserna and L. Rodriguez-Martinez, "Cycle ageing analysis of a LiFePO4/graphite cell with dynamic model validations: Towards realistic lifetime predictions," *Journal of Power Sources,* pp. 573-587, 2015.

[50] C. Dudézert, Y.Reynier, J.-M.Duffault and S.Franger, "Fatigue damageapproachappliedtoLi-ionbatteriesageing characterization," *Materials ScienceandEngineering,* p. 177–189, 2016.

[51] M. A. Tankari, M. B. Camara, B. Dakyo and G. Lefebvre, "Use of Ultracapacitors and Batteries for Efficient Energy Management in Wind–Diesel Hybrid System," *IEEE TRANSACTIONS ON SUSTAINABLE ENERGY,* 2013.

[52] M. Musallam and C. M. Johnson, "An Efficient Implementation of the Rainflow Counting Algorithm for Life Consumption Estimation," *IEEE TRANSACTIONS ON RELIABILITY,* pp. 978-986, 2012.

[53] T. Dragičević, H. Pandžić, D. Škrlec, I. Kuzle, J. M. Guerrero and D. S. Kirschen, "Capacity Optimization of Renewable Energy Sources and Battery Storage in an Autonomous Telecommunication Facility," vol. 5, 2014.

[54] WAAREE Energies Ltd., *WS-40 to WS-95 ARKA SERIES-Features,* Mumbai: WAAREE Energies Ltd.[manual].

[55] HHV SOLAR TECHNOLOGIES PVT. LTD., *CRYSTALLINE SOLAR PV MODULE: 250-300 WATT,* Bangalore: HHV SOLAR TECHNOLOGIES PVT. LTD.[manual].

[56] N. Narayan, N. Kretzchmar, J. Popovic-Gerber, J.-C. Diehl, P. Bauer and M. Zeman, "Bridging the gap between Base-of-Pyramid energy users and electrical system design: Stochastic load profile construction through mapping the energy demand and off grid tr," 2017 [unpublished].

[57] T. Urmee, D. Harries and H.-G. Holtorf, "Solar Home Systems—A Description of the Technology and Its Applications," in *Photovoltaics for Rural Electrification in Developing Countries*, Springer International Publishing Switzerland, 2016.

[58] L. Lam, *A Practical Circuit-based State of Health Estimation of Liion Battery Cells in Electric Vehicles,* Delft: TU DELFT [MSc thesis], 2011.

[59] H. Wenzl, I. Baring-Gould, R. Kaiser, B. Y. Liaw, P. Lundsager, J. Manwell, A. Ruddell and V. Svoboda, "Life prediction of batteries for selecting the technically most suitable and cost effective battery," vol. 144, 2005.

[60] V. Marioleas, *System Integration Project II,* Delft: [unpublished].

[61] Duracell, "Duracell Ni-MH Rechargeable batteries," Duracell, [Online]. Available: https://www.duracell.com/en-us/products/category/rechargeable-batteries-and-chargers/. [Accessed 10 January 2017 [manual]].

[62] B. Y. Liaw, E. P. Roth, R. G. Jungst, G. Nagasubramanian, H. L. Case and D. H. Doughty, "Correlation of Arrhenius behaviors in power and capacity fades with cell impedance and heat generation in cylindrical lithium-ion cells," *Journal of Power Sources,* Vols. 119-121, pp. 874-886, 2003.

[63] L. Lam and P. Bauer, "Practical Capacity Fading Model for Li-Ion Battery Cells in Electric Vehicles," *IEEE*

Transactions on Power Electronics, vol. 28, pp. 5910-5918, 2013.

[64] A. Nieslony, “Rainflow Counting Algorithm,” MathWorks, 04 April 2010. [Online]. Available: https://nl.mathworks.com/matlabcentral/fileexchange/3026-rainflow-counting-algorithm. [Accessed 28 May 2017].

[65] B. Dunn, H. Kamath and J.-M. Tarascon, “Electrical Energy Storage for the Grid: A Battery of Choices,” *Science,* vol. 334, no. 6058, pp. 928-935, 18 November 2011.

[66] P. V. d. Bossche, F. Vergels, J. V. Mierlo, J. Matheys and W. V. Autenboer, “SUBAT: An assessment of sustainable battery technology,” *Journal of Power Sources,* vol. 162, pp. 913-919, 2006.

[67] K. Hojckova, J. Jelinek, M. Schneider, N. Spittler and I. Varju, “Evaluation of battery storage technologies for sustainable and rural electrification in Sub-Saharan Africa,” 2015.

[68] X. Luo, J. Wang, M. Dooner and J. Clarke, “Overview of current development in electrical energy storage technologies and the application potential in power system operation,” *Applied Energy,* vol. 137, pp. 511-536, 2015.

[69] A. GREEN, “NICKEL CADMIUM BATTERIES FOR PHOTOVOLTAiC APPLICATIONS,” SAFT NIFE, INDUSTRIAL BATTERIES GROUP, Romainville, 1993.

[70] M. Kassem, J. Bernard, R. Revel, P. Serge, F. Duclaud and C. Delacourt, “Calendar aging of a graphite/LiFePO4 cell,” *Journal of Power Sources,* vol. 208, pp. 296-305, 2012.

[71] S. Grolleau, I. Baghdadi, P. Gyan, M. B. Marzouk and F. Duclaud, “Capacity fade of lithium-ion batteries upon mixed calendar/cycling aging protocol,” *World Electric Vehicle Journal ,* vol. 8, pp. 339-349, 2016.

[72] H. Zhang and M.-Y. Chow, “Comprehensive Dynamic Battery Modeling for PHEV Applications,” in *Power and Energy Society General Meeting, 2010 IEEE*, Minneapolis, 2010.

[73] M. Rashid and A. Gupta, “Effect of Relaxation Periods over Cycling Performance of a Li-Ion Battery,” *Journal of Electrochemical Society,* vol. 162, no. 2, pp. 3145-3153, 2015.

[74] D. Lalitha and H. Tingshu., “Effects of rest time on discharge response and equivalent circuit model for a lead-acid battery,” *Journal of Power Sources,* vol. 282, pp. 19-27, 2015.

[75] K. Williams, “Current Trends in the Energy Storage Market,” 7 July 2017. [Online]. Available: http://www.theenergycollective.com/willcoenergy/2408164/current-trends-energy-storage-market. [Accessed 15 August 2017].

[76] P. D’Aprile, J. Newman and D. Pinner, “McKinsey&Company,” August 2016. [Online]. Available: http://www.mckinsey.com/business-functions/sustainability-and-resource-productivity/our-insights/the-new-economics-of-energy-storage. [Accessed 15 August 2017].

[77] C. Claire, “Lithium-ion Battery Costs and Market,” Bloomberg New Energy Finance, 2017.

[78] O. Schmidt, A. Hawkes, A. Gambhir and I. Staffell, “The future cost of electrical energy storage based on experience rates,” *Nature Energy,* vol. 2, 2017.

[79] Electropaedia , “Electropaedia - Battery and Energy Technologies,” 2005. [Online]. Available: http://www.mpoweruk.com/nicad.htm. [Accessed 16 August 2017].

[80] The Swedish Environmental Protection Agency, “Cadmium in power tool batteries - The possibility and consequences of a ban,” The Swedish Environmental Protection Agency, Bromma, 2009 [file:///H:/My%20Documents/Downloads/Swedish-EPA-report-978-91-620-5901-9.pdf].

[81] N. D. W., “Solar energy storage: part 4 – Nickel-Batteries: NiCd,Nimh,NiFe,” Sinovoltaics Group Limited, 24 July 2015. [Online]. Available: http://sinovoltaics.com/solar-energy-storage/solar-energy-storage-part-4-nickel-batteries-nicdnimhnife/. [Accessed 20 August 2017].

[82] C. PILLOT, “The Rechargeable Battery Market and Main Trends 2014-2025,” Avicenne Energy, 2015.

[83] T. G. Goonan, “Lithium Use in Batteries,” U.S. Geological Survey Circular, Virginia, 2012.

[84] US Energy Information Administration, “Annual Energy Outlook 2012 with Projections to 2035,” US Energy Information Administration, Wahington DC, 2012.

[85] METALARY, “Lithium Price,” METALARY, 7 October 2017. [Online]. Available: https://www.metalary.com/lithium-price/. [Accessed 8 October 2017].

[86] Battery University , “What’s the Best Battery?,” Battey University , 21 3 2017. [Online]. Available: http://batteryuniversity.com/learn/archive/whats_the_best_battery. [Accessed 5 May 2017].

[87] P. Ruetschi, “Aging mechanisms and service life of lead–acid batteries,” *Journal of Power Sources,* vol. 127, p. 33–44, 2004.

Appendix A

- ***PM A RESULTS FOR ALL THE HB RATIOS***

Table 26: Hybrid Battery Cost Function (h.b.c.f) results for PMA and Case study 1 (low LP)

Battery Technology Combinations														
Ratio			**Hybrid Battery Cost Function [$*E+03]**											
			LiFePO4-main			**VRLA-main**			**NiCd-main**			**Flooded-main**		
Main [%]	**Second [%]**	**Ratio [-]**	VRLA	NiCd	Flooded	LiFePO4	NiCd	Flooded	LiFePO4	VRLA	Flooded	LiFePO4	VRLA	NiCd
10	90	9	1.12	1.46	1.26	1.21	1.82	1.51	1.59	1.88	2.04	1.25	1.43	1.88
20	80	4	1.17	1.18	1.19	1.65	1.76	1.78	2.62	2.76	2.88	1.77	1.89	1.99
30	70	2.33	1.28	1.18	1.28	2.12	2.10	2.11	3.66	3.75	3.77	2.34	2.33	2.33
40	60	1.5	1.31	1.22	1.31	2.44	2.25	2.35	4.55	4.54	4.55	2.75	2.72	2.64
50	50	1	1.28	1.13	1.28	2.59	2.36	2.51	5.23	5.16	5.20	2.92	2.84	2.76
60	40	0.67	1.27	1.15	1.27	2.64	2.46	2.58	5.55	5.49	5.49	3.09	3.02	2.91
70	30	0.43	1.23	1.15	1.23	2.70	2.56	2.65	5.86	5.81	5.81	3.15	3.11	3.02
80	20	0.25	1.30	1.24	1.30	2.71	2.62	2.68	6.12	6.08	6.08	3.30	3.27	3.21
90	10	0.1	1.23	1.20	1.23	2.77	2.73	2.76	6.54	6.52	6.52	3.34	3.32	3.21
Minimum Value			1.12	1.13	1.19	1.21	1.76	1.51	1.59	1.88	2.04	1.25	1.43	1.88

Table 27: Hybrid Battery Cost Function (h.b.c.f) results for PMA and Case study 2 (medium LP)

Battery Technology Combinations														
Ratio			**Hybrid Battery Cost Function [$*E+03]**											
			LiFePO4-main			**VRLA-main**			**NiCd-main**			**Flooded-main**		
Main [%]	Second. [%]	Ratio [-]	VRLA	NiCd	Flooded	LiFePO4	NiCd	Flooded	LiFePO4	VRLA	Flooded	LiFePO4	VRLA	NiCd
10	90	9	4.52	5.80	4.72	3.00	6.51	5.10	3.6	5.31	5.76	3.07	4.99	6.59
20	80	4	3.53	4.32	3.83	3.28	4.99	4.48	4.16	5.39	5.51	3.41	4.33	5.14
30	70	2.33	3.48	4.18	3.75	3.28	5.01	4.58	4.47	5.28	5.57	3.68	4.49	5.19
40	60	1.5	3.43	4.04	3.67	3.80	5.09	4.74	4.95	5.63	5.88	4.02	4.70	5.31
50	50	1	3.35	3.88	3.41	4.11	5.18	4.71	5.58	6.14	6.19	4.25	4.80	5.33
60	40	0.67	3.31	3.60	3.35	4.47	5.17	4.94	6.46	6.86	6.91	4.80	5.24	5.66
70	30	0.43	3.16	3.49	3.30	4.84	5.36	5.18	7.3	7.61	7.63	5.25	5.44	5.76
80	20	0.25	3.15	3.23	3.17	5.15	5.42	5.36	8.47	8.58	8.67	5.64	5.83	5.91
90	10	0.1	3.15	3.15	3.18	5.92	5.96	5.97	10.06	10.11	10.12	6.50	6.54	6.58
Minimum Value			3.15	3.15	3.17	3.00	4.99	4.48	3.36	5.28	5.51	3.07	4.33	5.14

- ***PM B RESULTS FOR ALL THE HB RATIOS***

Table 28: Hybrid Battery Cost Function (h.b.c.f) results for PMB and Case study 1 (low LP)

Battery Technology Combinations														
Ratio			Hybrid Battery Cost Function[$*E+03]											
			LiFePO4-main			VRLA-main			NiCd-main			Flooded-main		
Main [%]	Second. [%]	Ratio [-]	VRLA	NiCd	Flooded	LiFePO4	NiCd	Flooded	LiFePO4	VRLA	Flooded	LiFePO4	VRLA	NiCd
50	50	1	3.75	5.65	3.97	3.96	7.08	5.40	6.49	7.73	8.02	4.34	5.57	7.59
60	40	0.67	3.49	5.21	3.75	4.32	6.98	5.50	7.27	8.13	8.43	4.81	5.59	7.47
70	30	0.43	3.14	4.69	3.35	4.77	6.68	5.36	7.93	8.76	8.84	5.01	5.71	7.18
80	20	0.25	3.11	3.89	3.19	4.93	6.06	5.38	9.11	9.37	9.56	5.66	5.91	6.69
90	10	0.1	3.04	3.33	3.08	5.46	5.91	5.64	10.24	10.31	10.35	6.19	6.29	6.60
Minimum Values			3.04	3.33	3.08	3.96	5.91	5.36	6.49	7.73	8.02	4.34	5.57	6.60

Table 29: Hybrid Battery Cost Function (h.b.c.f) results for PMB and Case study 2 (medium LP)

Battery Technology Combinations														
Ratio			Hybrid Battery Cost Function [$*E+03]											
			LiFePO4-main			VRLA-main			NiCd-main			Flooded-main		
Main [%]	Second. [%]	Ratio [-]	VRLA	NiCd	Flooded	LiFePO4	NiCd	Flooded	LiFePO4	VRLA	Flooded	LiFePO4	VRLA	NiCd
50	50	1	9.29	14.68	9.90	9.90	18.41	13.48	15.48	18.41	19.00	10.83	13.80	19.38
60	40	0.67	8.71	12.48	9.13	10.93	17.11	13.51	18.17	20.21	20.71	12.36	14.31	18.53
70	30	0.43	8.21	10.92	8.57	12.22	16.14	13.64	19.92	21.45	21.86	13.58	14.63	17.75
80	20	0.25	7.68	9.44	8.01	12.64	15.13	13.72	21.97	22.73	22.71	14.11	14.89	16.60
90	10	0.1	7.13	7.84	7.20	13.26	14.30	13.64	23.39	23.65	23.75	14.90	15.24	15.89
Minimum Values			7.13	7.84	7.20	9.90	14.30	13.48	15.48	18.41	19.00	10.83	13.80	15.89

- ***Battery Miscellaneous***

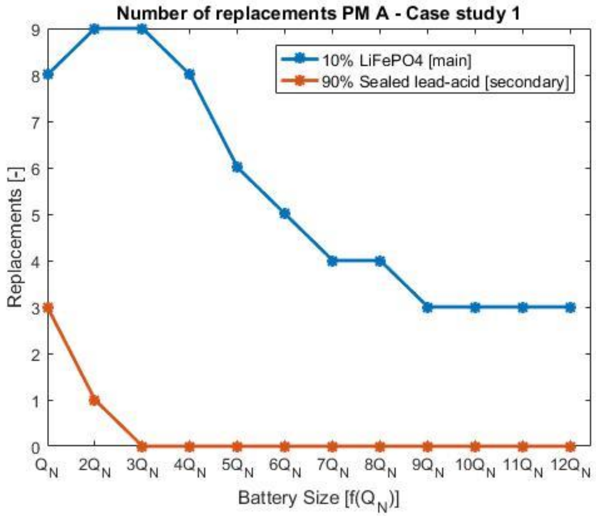


Figure A-1: Number of replacements for battery oversizing in PMA-Case study1

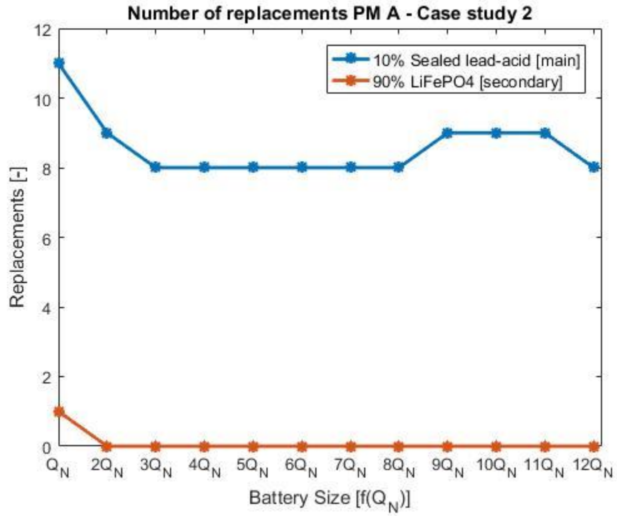


Figure A-2: Number of replacements for battery oversizing in PMA-Case study2

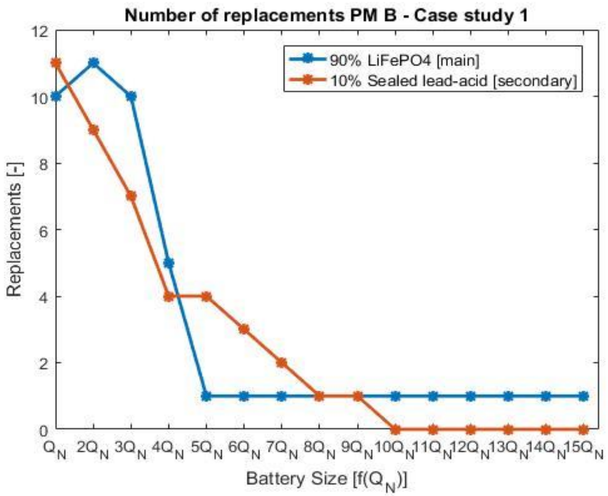


Figure A-3: Number of replacements for battery oversizing in PM B-Case study1

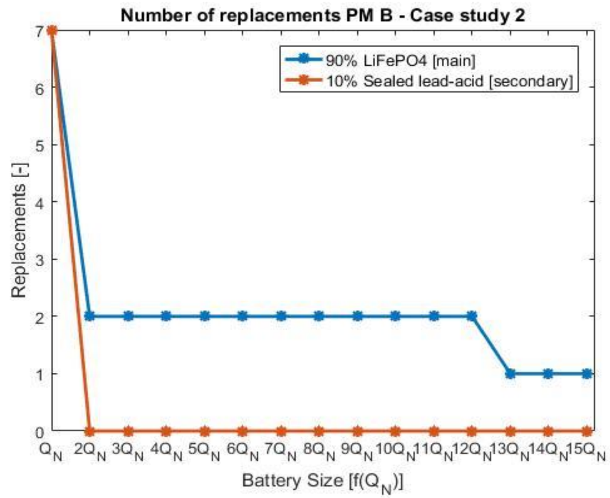
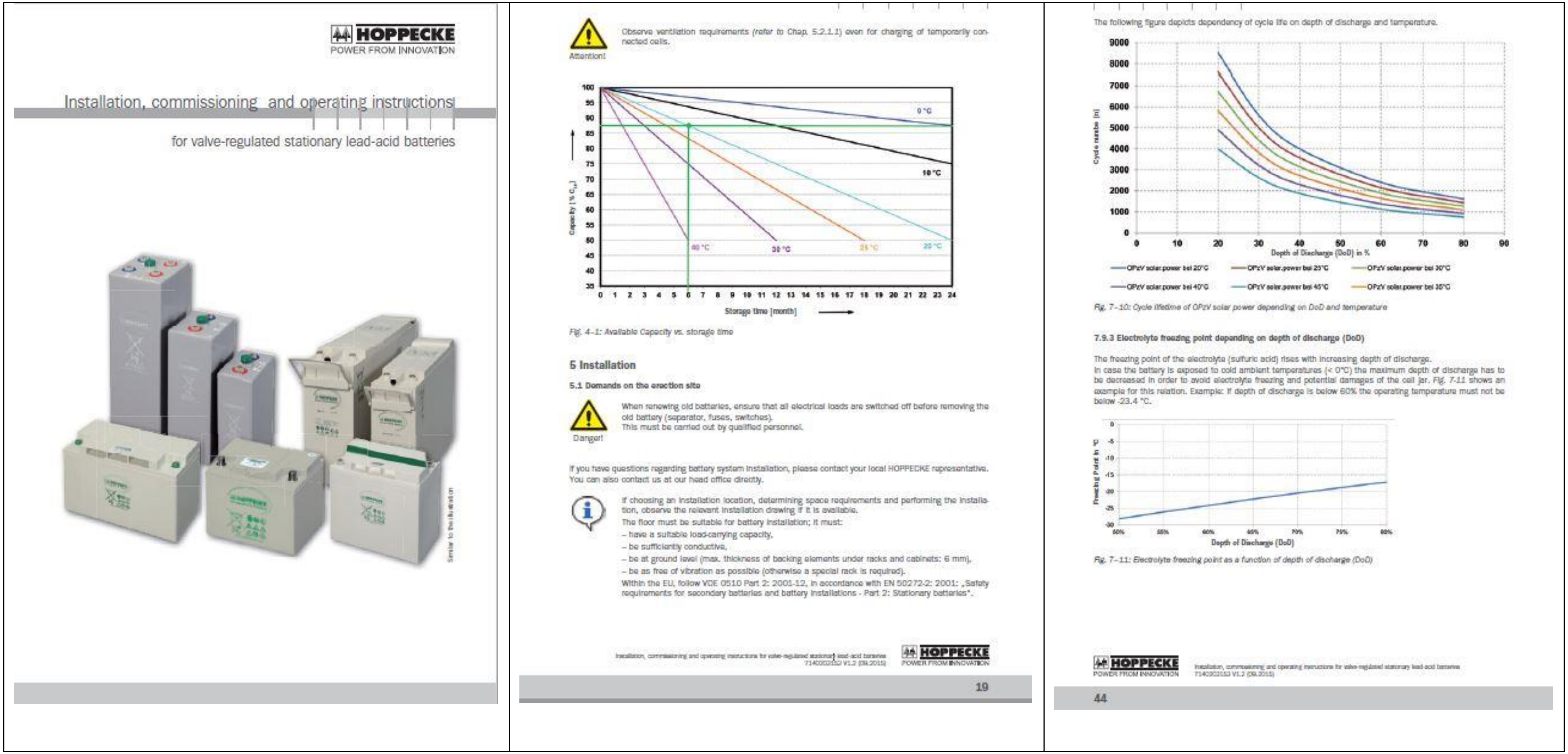


Figure A-4: Number of replacements for battery oversizing in PM B-Case study2

Appendix B

- ***Sealed lead-acid***



HOPPECKE
POWER FROM INNOVATION

Installation, commissioning and operating instructions

for valve-regulated stationary lead-acid batteries

Attention!

Observe ventilation requirements (refer to Chap. 5.2.1.1) even for charging of temporarily connected cells.

Fig. 4–1: Available Capacity vs. storage time

5 Installation

5.1 Demands on the erection site

Danger!

When renewing old batteries, ensure that all electrical loads are switched off before removing the old battery (separator, fuses, switches).
This must be carried out by qualified personnel.

If you have questions regarding battery system installation, please contact your local HOPPECKE representative. You can also contact us at our head office directly.

If choosing an installation location, determining space requirements and performing the installation, observe the relevant installation drawing if it is available.
The floor must be suitable for battery installation; it must:
– have a suitable load-carrying capacity,
– be sufficiently conductive,
– be at ground level (max. thickness of backing elements under racks and cabinets: 6 mm),
– be as free of vibration as possible (otherwise a special rack is required).
Within the EU, follow VDE 0510 Part 2: 2001-12, in accordance with EN 50272-2: 2001: „Safety requirements for secondary batteries and battery installations - Part 2: Stationary batteries".

19

The following figure depicts dependency of cycle life on depth of discharge and temperature.

Fig. 7–10: Cycle lifetime of OPzV solar power depending on DoD and temperature

7.9.3 Electrolyte freezing point depending on depth of discharge (DoD)

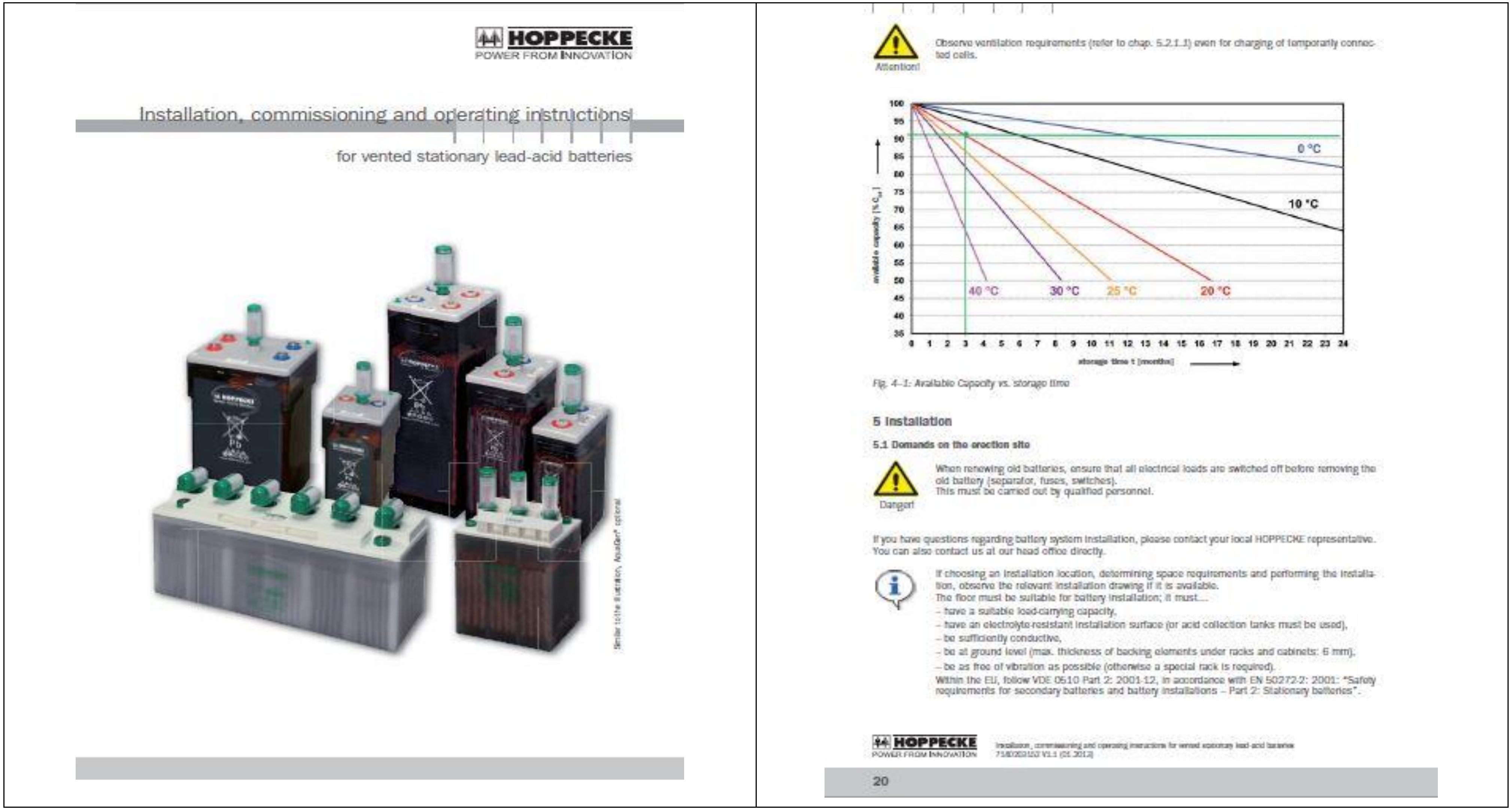
The freezing point of the electrolyte (sulfuric acid) rises with increasing depth of discharge.
In case the battery is exposed to cold ambient temperatures (< 0°C) the maximum depth of discharge has to be decreased in order to avoid electrolyte freezing and potential damages of the cell jar. Fig. 7-11 shows an example for this relation. Example: If depth of discharge is below 60% the operating temperature must not be below -23.4 °C.

Fig. 7–11: Electrolyte freezing point as a function of depth of discharge (DoD)

44

[Sourced from [36]*]*

- ***Flooded lead-acid***


HOPPECKE
POWER FROM INNOVATION

Installation, commissioning and operating instructions
for vented stationary lead-acid batteries

Attention!
Observe ventilation requirements (refer to chap. 5.2.1.1) even for charging of temporarily connected cells.

Fig. 4–1: Available Capacity vs. storage time

5 Installation

5.1 Demands on the erection site

Danger!
When renewing old batteries, ensure that all electrical loads are switched off before removing the old battery (separator, fuses, switches).
This must be carried out by qualified personnel.

If you have questions regarding battery system installation, please contact your local HOPPECKE representative. You can also contact us at our head office directly.

If choosing an installation location, determining space requirements and performing the installation, observe the relevant installation drawing if it is available.
The floor must be suitable for battery installation; it must...
– have a suitable load-carrying capacity,
– have an electrolyte-resistant installation surface (or acid collection tanks must be used),
– be sufficiently conductive,
– be at ground level (max. thickness of backing elements under racks and cabinets: 6 mm),
– be as free of vibration as possible (otherwise a special rack is required).
Within the EU, follow VDE 0510 Part 2: 2001-12, in accordance with EN 50272-2: 2001: "Safety requirements for secondary batteries and battery installations – Part 2: Stationary batteries".

HOPPECKE
POWER FROM INNOVATION

20

[Sourced from [37]*]*

- ***NiCd***

Power

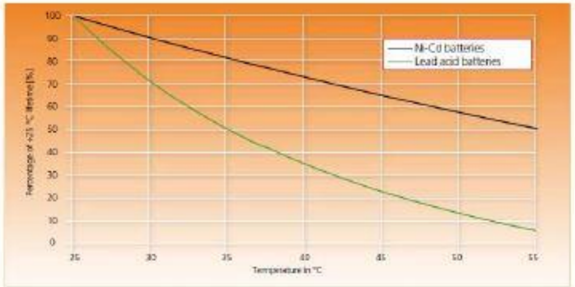
Industrial Ni-Cd Batteries Standard Range
Technical Manual

Effective: October, 2009

Alpha Technologies

4.5 Impact of Temperature on Lifetime

As with every battery system an increased temperature always reduces the expected service lifetime and although the Alpha Ni-Cd battery is designed to reach a lifetime of over 20 years this is also the case. The following graph is included to demonstrate that the reduction in lifetime of a Alpha Ni-Cd battery is many times lower than for a lead acid battery. For Ni-Cd batteries the normal operating temperature is based at + 20 °C (± 5 °C) and, therefore, special considerations have to be taken into account when dimensioning a Ni-Cd battery for high temperature applications.



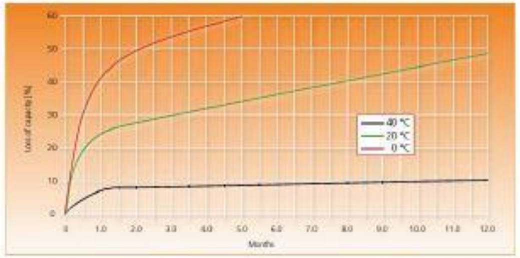
Graph 4-2, NiCd vs. Pb-acid battery lifetimes at higher temperatures as a percentage of operational lifetime at 25°C

4.6 Short-circuit values

The short-circuit values of a Alpha Ni-Cd pocket plate battery depend on and vary from cell range to cell range. The special values can be provided by our technical staff on request.

4.7 Open Circuit Loss

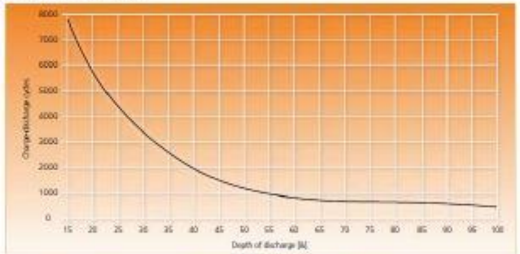
The state of charge of a Ni-Cd cell on open circuit slowly self-discharges. Ni-Cd batteries are affected significantly by temperature. The higher the temperature, the higher loss of capacity. Ni-Cd batteries self-discharge at a niminal rate of 2% per month at 20°C.



Graph 4-3, Self-discharge of NiCd-accumulators (fully charged)

4.8 Cycling

The Alpha Ni-Cd battery is designed to obtain a huge number of cycles in stationary standby operations. The important fact and basis for the number of cycles the battery is able to provide is the depth of discharge. The less deeply a battery is discharged the greater the number of cycles it is capable to provide before being unable to achieve the minimum design limit. On the graph below typical values for the effect of depth of discharge on the available cycle life can be found.



Graph 4-4, Cycle life vs. depth of discharge as a percentage of rated battery capacity @ 20°C

[Sourced from [40]*]*

- ***LiFePO4***

10/16/2017 Long Cycle Life Lithium Iron Magnesium Phosphate Battery

Long Cycle Life

Valence's Lithium Iron Magnesium Phosphate Battery has a long cycle life

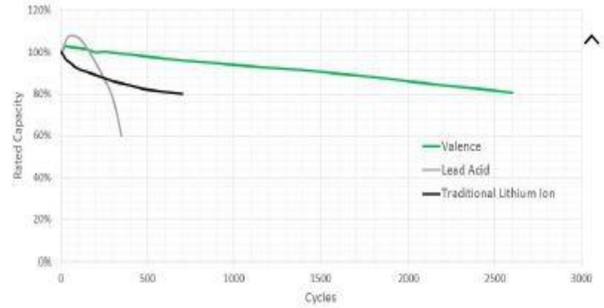
Traditionally, the cycle life of a battery is the number of cycles of charge and discharge a battery can undergo while still retaining 80 percent of its initial capacity. The 80% limit is a legacy value left over from lead acid battery testing because once a lead acid battery has reached 80% of original capacity, it may exhibit sudden death as the capacity can decrease rapidly thereafter.

As a result of our stable, high-quality chemistry, the Valence product line has superior cycle life compared to lead acid and lithium mixed oxide batteries. Valence batteries have a slow predictable fade with no sudden drop in capacity. In fact, one can now use the battery until the energy drops below that needed in an application rather than arbitrarily stop at 80%. Valence lithium ion batteries can keep supplying energy down to 70%, 60% or even 50% of original capacity. And even then, they could be transitioned to another application where the rest of the capacity could still be useful. This benefit is just not offered with lead acid.

As a result of our stable, high-quality chemistry, the Valence product line has superior cycle life compared to both lead acid and lithium mixed oxide batteries as illustrated in the graphic below:

https://www.valence.com/why-valence/long-lifecycle/ 1/3

10/16/2017 Long Cycle Life Lithium Iron Magnesium Phosphate Battery



100% Depth of Discharge at C/2

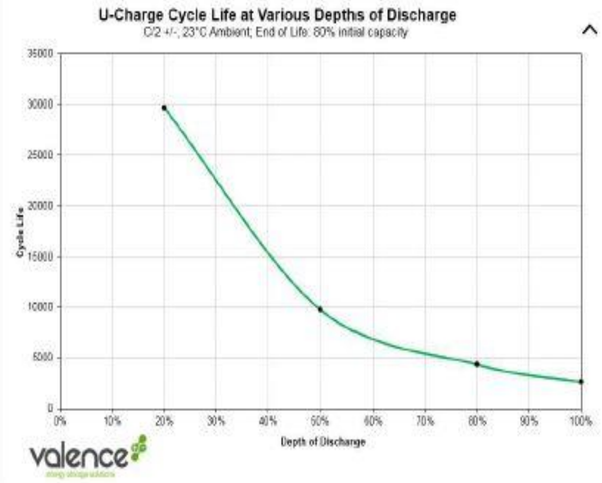
The lithium-ion battery works on ion movement between the positive and negative electrodes. In theory such a mechanism should work forever, but cycling, elevated temperature and aging decrease capacity over time. Manufacturers take a conservative approach and specify the life of Li-ion in most consumer products as being between 300 and 500 discharge/charge cycles. A battery may fail before that time due to heavy use or unfavorable temperature conditions. Valence's lithium iron magnesium phosphate battery lasts thousands of cycles. This is why it's an ideal solution for industrial deep-cycle batteries.

Valence Lithium Iron Magnesium Phosphate Battery and Depth of Discharge

Very few applications discharge the battery down to 100% Depth of discharge (DoD). If they do, they severely hurt cycle life of lead acid or LCO batteries. Valence batteries can be discharged to any DoD without any harm. Since applications can vary their DoD, cycle life varies as well. Notice that changing from 100% to 80% DoD doubles the cycle life. And one can double it again from 80% to 50% DoD. Energy throughput is still exceptional no matter what DoD the battery experiences. Partial discharge on Valences' lithium iron magnesium phosphate battery is fine. There is no memory and the battery does not need periodic full discharge cycles to prolong life.

The below graphic highlights our cycle life based upon Depth of Discharge usage:

10/16/2017 Long Cycle Life Lithium Iron Magnesium Phosphate Battery



[Sourced from [41]*]*

Appendix C

Paper Title: *A simple methodology for assessing battery lifetimes in Solar Home System Design*

Authors: Nishant Narayan, Thekla Papakosta, Victor Vega-Garita, Jelena Popovic-Gerber, Pavol Bauer, and Miro Zeman.

Accepted and presented at the conference: IEEE AFRICON 2017, Cape Town
Won the "Outstanding paper Award" in 19th of September 2017

A simple methodology for assessing battery lifetimes in Solar Home System Design

Nishant Narayan[a], Thekla Papakosta[a], Victor Vega-Garita[a], Jelena Popovic-Gerber[a], Pavol Bauer[a], and Miro Zeman[a]
[a]Delft University of Technology, Department of Electrical Sustainable Energy, P.O. Box 5031, 2600 GA, Delft, The Netherlands
Email: N.S.Narayan@tudelft.nl

***Abstract*— The proliferation of Solar Home Systems (SHS) in recent times hopes to provide an alleviating solution to the global problem of energy poverty. Battery is usually the most expensive but important part of an SHS; it is also normally the first part to fail. Estimating the battery lifetime can help make informed system design choices, and it is therefore an important exercise for an SHS designer. Battery lifetime modelling is often a complex task requiring empirical data or reliance on modelling cell level electrochemical phenomena. This paper presents a simple battery lifetime estimation method specific to the application and candidate battery choices at hand. An SHS application specific simulation is carried out for a year and the effect of micro-cycles on the battery activity is analyzed. The concept of active Depth-of-Discharge (DOD) is introduced. Cyclic ageing of the battery is thus quantified and relative cycle lives of 2 battery technologies are compared. A delicate trade-off is demonstrated between battery sizing and lifetime. The described methodology is also compared with an empirical model and the lifetime results are found to be within 3.85%. The methodology described in this paper can potentially help SHS designers in making quick, reasonable estimations of battery lifetimes based on the intended application and battery manufacturer's data.**

***Keywords*—Battery lifetime estimation, cyclic ageing, battery lifetime model, battery sizing, Solar Home Systems.**

I. Introduction

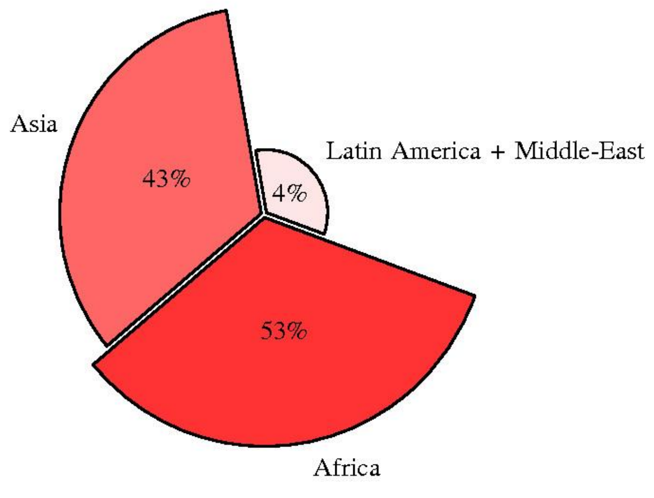


Fig. 1. Geographical split of global population without electricity (data sourced from [1]).

978-1-5386-2775-4/17/$31.00 ©2017 IEEE

As of 2016, an estimated 1.2 billion people around the world lacked access to electricity, with around 85% of them living in the rural areas [1]. Figure 1 shows the distribution of the electricity-deficient population around the world.

For multiple reasons, most of the unelectrified rural areas in these regions have hitherto not received grid-based electricity [2]. While the national grid extension may not be the most viable and immediate solution to rural electrification [3] [4], Solar Home Systems (SHS) appear to be a promising pathway to address the pressing electricity needs. The fact that most of these regions lie in the sunny latitude belts also underline the usefulness of solar-based solutions [2].

A Solar Home System is defined as a Photovoltaic (PV)-based generator rated usually between 50 Wp to 250 Wp, accompanied by a suitable battery storage [5]. In some cases, the rated PV size can be higher, up to 500 Wp [6]. However, these usually tend to be not at a rural household level but a neighborhood or community level. The various upfront SHS component-costs have been illustrated in Figure 2.

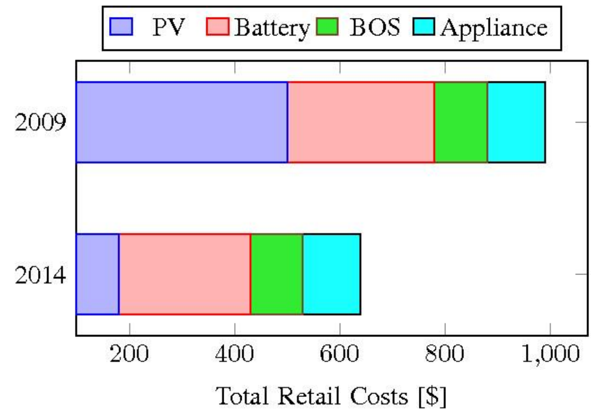


Fig. 2. Split-up of initial costs of SHS components in 2009 and 2014 for powering a 19" TV, radio, lights and a mobile phone charger (data from [7]).

The PV costs have fallen considerably between 2009 and 2014, but the battery costs are more or less the same, similar to the Balance of System (BOS) and appliance-costs. However, what makes the battery-costs more relevant is the sizable proportion of the upfront SHS costs, coupled with the fairly low lifetime of the batteries. For instance, the expected lifetime of the lead-acid batteries used in the SHS can be as low as 3 years [5], compared to the lifetime of a regular PV module to be around 25 years. Even though some of the more efficient batteries may last longer, they would still need the occasional replacement in the lifetime of the SHS [2]. Thus, the battery can be seen as usually the first to fail and increasingly the most expensive SHS component.

Moreover, the accurate sizing of the battery can have an impact of the battery lifetime [2]. This is because an increase in battery size for the same application reduces the average Depth of Discharge (DOD) for the battery [8], as seen below in Section II. Therefore, the sizing of the battery in an SHS presents itself as an interesting balance between upfront costs (size) and lifetime.

In this light, battery lifetime is seen as a vital parameter to be borne in mind when designing an SHS, especially in Base-of-Pyramid (BoP) context of usage. This work strives to estimate the battery lifetime in a simple yet reasonably accurate way based on anticipated SHS usage and battery data provided by the manufacturer.

Outline of the paper

This paper is divided into five sections. Section I introduces the work described in the paper, while Section II outlines the necessary technical background and the focus of this study. Section III describes the methodology used and the related dependencies on the different kinds of data. The results are discussed in Section IV and the relevance of these results in the specific case of SHSs is illustrated. Finally, Section V concludes the discussion on the battery lifetime estimation methodology, along with the necessary recommendations and future work that will build upon and extend the efforts described in this paper.

II. Battery lifetime

A. *Battery parameters*

State of Charge (SOC) and Depth of Discharge (DOD): The state of charge (SOC) indicates battery capacity as a fraction of the initial capacity, while the depth of discharge (DOD) refers to the capacity discharged as a percentage of the initial capacity. They are a complement of each other.

The DOD can be calculated from the battery discharge current over a discharging interval as shown in Equation 1.

$$DOD = \frac{\int_{t_i}^{t_f} I_{discharge}.dt}{C_i} \tag{1}$$

where t_f is the time at the end of the discharge interval process, t_i is the initial time, $I_{discharge}$ is the current, and C_i the initial battery capacity.

Cycle-life: Cycle-life is defined as the number of charge/discharge cycles that a battery can undergo maintaining a specified percentage of its initial capacity, after which batteries reach the end of life (EoL). The EoL is usually defined as 80% of the initial nominal battery capacity [9].

The battery ageing can be classified into two categories. These are:

Cyclic ageing: Cyclic ageing is related to the decrease in battery capacity while the battery is undergoing cycling. Cyclic ageing plays a larger role in cases where operation times are relatively longer than idle periods.

Calendar ageing: Calendar ageing is related to the decrease in battery capacity while under storage and not in use, and therefore, independent of charge/discharge cycles. Calendar ageing plays a predominant role in cases where operation times are more shorter than idle periods, but also in cases of shallow cycling and low C-rates [10].

B. *Causes of battery failure*

Battery lifetime is influenced by many factors: average DOD, temperature, charge/discharge rates, charge/discharge profiles, and cut-off voltage. The kinetics of the chemical reaction taking place inside the batteries is dictated by the temperature and charge/discharge rates. Therefore, when both C-rate and temperature increase, battery lifetime diminishes drastically [11]. DOD operation range also influences performance degradation, and as a general rule it is always preferred to operate in the plateau region of the Voltage Vs SOC curve. This avoids overcharge (high voltages) or over-discharge (low voltages), which can otherwise cause electrolytes to degrade faster under these conditions [9].

Due to the different side reactions, batteries age but they also can suddenly fail, by phenomena like cell cycling, short circuits, and thermal runaway [9]. For lithium-ion batteries, the main reason for battery degradation is the loss of active lithium principally at the anode, caused by mechanical stresses which lead to volume changes increasing the internal cell impedance and eventually removing active material [10]. The normal undesired side reactions that occur for lithium-ion batteries are electrode pore clogging, passive layer growth, and lithium metal plating [12]. Whereas for lead-acid batteries, battery degradation is caused by the anodic corrosion of grids, plate straps posts, active mass degradation, and loss of adherence to the grid. Moreover, the loss of water and crystallization that form lead sulphate in the active mass of the material induce further the ageing process [13].

C. *Mapping failure mechanisms to lifetime models*

While experimental methods observe and measure the battery degradation through time, semi-empirical approaches represent the fade mechanisms using equations that fit a particular type of cell. Theoretical analyses are also implemented including the physiochemical effects behind the side reactions of a particular set of chemical compounds. Therefore, the main limitation of all of these approaches is that they are constructed for specific cells, under certain environment conditions, and tested through a limited amount of time [14]. This not only costs time per use-case and application needed but also puts under scrutiny the accuracy of these approaches if they were to be used under a different set of conditions or applications.

This paper focuses on a non-empirical approach for estimating the lifetime of the battery, where relevant battery parameters like DOD and number of cycles are extracted from battery manufacturers datasheets. Note that while the approach described here is non-empirical, the battery data relied on from the manufacturer can, however, be empirical in nature. As a consequence, we are able to estimate battery lifetime for various battery technologies and makes for a specific application. This method was applied for an SHS application case, accounting for the cycling that the battery undergoes and its impact on battery lifetime

III. Methodology

The methodology consists of multiple stages, as described below.

A. *Battery data from the manufacturer*

Battery manufacturers usually provide the battery cycle-life characteristics as a function of DOD [15]. First, this curve is extracted from the manufacturer's datasheet and a lookup-table is created. A reconstruction of the battery lifetime curves from the battery datasheet is shown in Figure 3. This curve is then approximated as a polynomial function that can be used in battery lifetime estimation based on the application-specific battery usage.

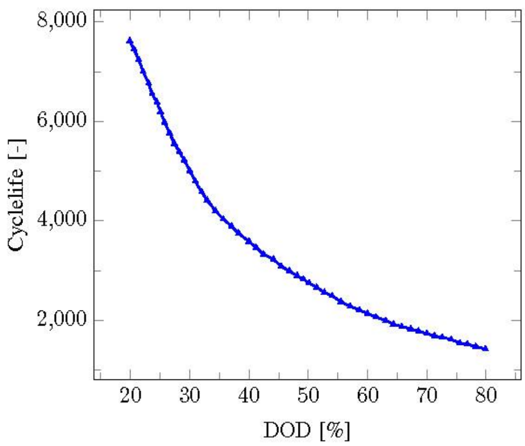


Fig. 3. Reconstruction of battery cycle-life curves based on DOD for sealed lead-acid battery(data sourced from [15]).

Battery technology: Two battery technologies are chosen for this study, viz., Lead-acid (sealed) or lead-acid gel battery, and Lithium-ion battery.

Polynomial approximations: The 4th order polynomial approximation for the battery lifetime curves for the above-mentioned technologies is given by Equation 2.

$$n = p_4.d^4 + p_3.d^3 + p_2.d^2 + p_1.d + p_0 \qquad (2)$$

Where:
p_0 to p_4: coefficients of the polynomial function,
d: battery DOD,
n: cycle-life the battery enjoys at the particular DOD.
The coefficients p_0 to p_4 for the 2 battery technologies are mentioned in Table I.

TABLE I
Polynomial coefficients for cycle-life Vs DOD curves for sealed lead-acid and lithium ion battery(data sourced from [16] and [17]).

Coefficients	**Sealed Lead Acid**	**Lithium Ion**
p_0	2.01E+04	1.84E+05
p_1	-9.67E+04	-1.16E+06
p_2	2.14E+05	2.88E+06
p_3	-2.27E+05	-3.21E+06
p_4	9.20E+04	1.34E+06

B. *SHS application and load profile*

A Solar Home System application was considered for estimating the battery lifetime.

a) Load profile: A load profile was constructed based on forecasting the future needs of BoP based communities in the future [8], especially taking into account the efficient DC appliances that are on the rise in the off-grid market. Several works in the recent past suggest a sharp rise in availability as well as popularity of the so-called super-efficient DC appliances [18] [19] [20]. The future load profile used in this study uses such efficient DC appliances comprising of lights, fan, mobile phone chargers, LCD TV, radio, water kettle, rice cooker, fridge, and an iron. The daily load profile has been plotted in Figure 4.

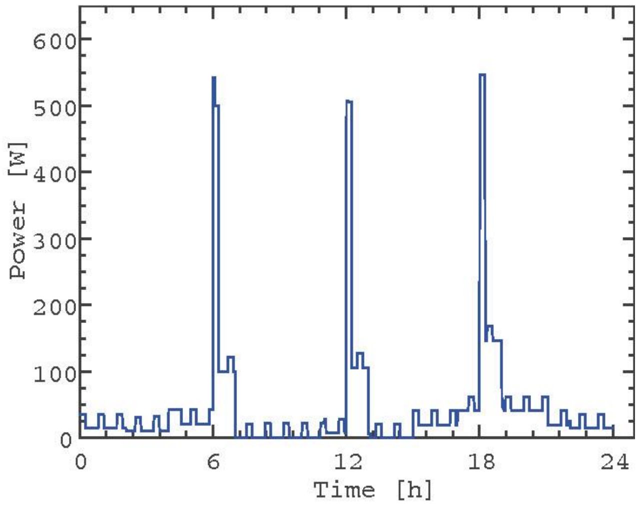


Fig. 4. Daily load profile of an off-grid household to be powered by an SHS.

b) SHS system parameters: The following SHS system parameters were considered.

- PV size: 300 Wp.
- Battery size: 1150 Wh.

This PV-battery combination guaranteed a Loss-of-Load probability (LLP) of 0 for the given load profile, i.e., this was the minimum storage size with the required PV size that could guarantee no loss of load throughout the 1 year of simulation. LLP is a metric defined as the ratio of the expected amount of time the system fails to deliver the demanded power, to the total amount of time the system was designed to deliver power for. The concept of LLP has been explained in a previous work in [8].

c) SHS simulation: A simple power flow-based model was constructed in MATLAB. The meteorological inputs to the model were obtained from the tool Meteonorm [21]. A sample geographical location experiencing an average of 5.5 equivalent sun hours per day was considered. The data resolution of the inputs to the model was 1 minute. Considering the load profile and SHS size as described above, an annual simulation was run over an arbitrary calendar year to obtain the battery usage pattern. It should be noted that the battery was limited to a maximum DOD limit of 80% in the simulation.

C. Battery lifetime estimation through battery usage

Based on the kind of cycling the battery undergoes for the application scenario considered in this study, useful battery parameters like average SOC, average DOD, and total battery energy throughput are extracted from the simulation.

Battery energy throughput: This is the total amount of energy that the battery cycles over a certain period of time. The total battery energy throughput in this context is thus the total amount of energy that the battery cycles over the one year that the SHS application is simulated over.

Concept of active DOD/SOC: Usually the DOD/SOC is considered taking into account the battery activity throughout the simulation. However, there are several time intervals when the battery is NOT in operation. Therefore, the effective cycling that contributes to the capacity fading are far fewer than considered in most studies. Consequently, the concepts of active SOC and active DOD are introduced. Active SOC/DOD refers to the State-of-Charge or Depth-of-Discharge of the battery while the battery is in operation. It may be noted that the active DOD based battery lifetime estimation investigated in this study using the battery manufacturer's data only considers the cyclic ageing and not calendar ageing. Moreover, the lifetime curves obtained from the datasheet corresponded to a temperature of 25°C, a reasonably usual average temperature in the tropical belt that is an intended target of such a battery inclusive Solar Home System.

1) Coarse battery lifetime estimation: This is a quick battery lifetime estimation method based on overall DOD and energy throughput. The average active DOD is obtained from the simulation along with the total battery energy throughput. The battery cycle-life is then estimated from Equation 2 using the average DOD for d. Consequently, the battery lifetime is calculated as shown in Equation 3.

$$L = n \times DOD_{avg} \times \frac{2 \times E_{nom}}{E_{thr,tot}} \tag{3}$$

Where L = battery lifetime in years, n = cycle-life, DOD_{avg} = average active DOD, E_{nom} = Nominal battery capacity, $E_{thr,tot}$ = Total energy throughput of the battery.

2) Zero-crossing based battery lifetime estimation: The coarse estimation relies on an average DOD that does not capture the whole story of the battery cycling, especially where short, deep current cycles are concerned. Therefore, it is better to consider the effect of all the micro-cycles that constitute the overall battery cycling. In this context, a micro-cycle is defined as a small cycle of variable duration that exists between two consecutive current zero crossings, usually much shorter than a full charge-discharge cycle. This method involves taking into account all the zero current transitions that the 1 minute data resolution allows. Although far from instantaneous, it is assumed that a one minute data resolution provides a reasonable accuracy to incorporate the intermittency of the PV generation and the load profile.

Figure 5 illustrates this concept. In this case, the active DOD should only be considered for the durations that the battery is cycling. The area of each micro-cycle times the corresponding voltage gives the energy that the battery cycles in that interval. As seen in Figure 5, the states with $I_{battery} = 0$ are ignored. Finally, the overall DOD can be calculated as shown in Equation 4.

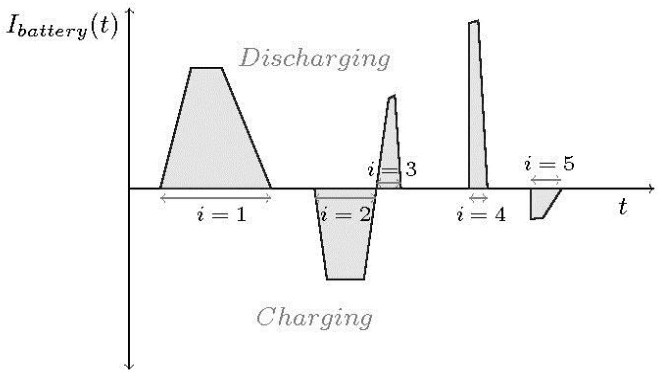


Fig. 5. An illustrative battery current waveform showing arbitrary micro-cycle intervals. i is the micro-cycle number.

$$\overline{DOD} = \frac{\sum_{i=1}^{N} \overline{DOD_i}.E_{thr_i}}{\sum_{i=1}^{N} E_{thr_i}} \tag{4}$$

Where $\overline{DOD}$: Combined average active DOD due to all the micro-cycles, $\overline{DOD_i}$: Average active DOD in the i^{th} micro-cycle, E_{thr_i} : Total energy throughput in the i^{th} micro-cycle.

This method estimates the average active DOD taking all the microcycles into account. Once the $\overline{DOD}$ is known, the cycle lifetime can be estimated as described in Equation 5.

$$L = n \times \overline{DOD} \times \frac{E_{nom}}{E_{thr,tot}} \tag{5}$$

Where the different variables are as described in equations 3 and 4. In this way, the impact of all the different micro-cycle activity occurring at various DOD levels is considered.

IV. Results

As described in Section III, an SHS application with the aforementioned PV and battery size was simulated for one year on MATLAB. The results of the battery usage for such a scenario are tabulated below.

A. Battery usage statistics

Due to the intermittent nature of solar irradiance, and the variations in the load profile, the battery undergoes charging and discharging at different levels of SOC and DOD throughout the year.

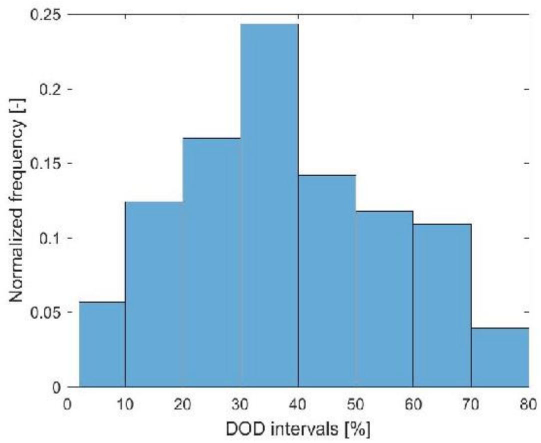


Fig. 6. Histogram with normalized frequency showing all DOD values.

Figure 6 shows a histogram that captures the different DOD levels experienced by the battery. However, Figure 7 shows a histogram of only the active DOD levels, i.e. the DOD levels at which the battery was experiencing a charging of discharging (micro-)cycle. This was done after analyzing the micro-cycle level battery cycling data based on the zero-crossings, as described in Section III-C. As seen, the two histograms greatly vary, especially in the range of 0 to 40% DOD. The differences in Figure 6 underline the periods of inactivity of the battery when it was either full, or not needed to power the load. Note that the frequency denoted in the histograms have been normalized to make a relative comparison easier. Moreover, the histogram for normal DOD values (refer Figure 6) in the range of 0 to 0.02 are ignored, because the battery has a disproportionate amount of 'full' battery times in the SHS system size considered. Additionally, the lower limit of the battery SOC was fixed at 20% for the duration of the simulation, which explains why the maximum limit of the DOD shown in the histogram is 80%.

The following important battery parameters were obtained through the SHS simulation, as shown in Table II.

As seen in Table II, there is a significant difference between the average DOD and the average active DOD obtained from the zero-crossing based estimation. A total energy throughput

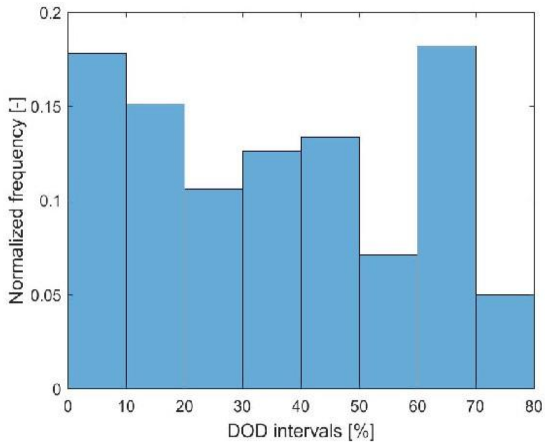


Fig. 7. Histogram with normalized frequency showing active DOD values.

TABLE II
Battery usage statistics as obtained through the SHS simulation.

Parameter	Value
Energy throughput (kWh)	626
Average DOD	0.333
Average Active DOD	0.360

of 626 kWh is experienced by the battery through the one year of simulation for the SHS application.

B. Cycle-life estimation

Based on the battery usage statistics shown in Table II, and the lifetime estimation methodologies described in III-C, the cycle-life of the SHS battery for two different technologies is calculated. The result is tabulated in Table III. It can be seen that Lithium ion based battery clearly enjoys a much higher life-time for the intended application. Additionally, the difference in the lifetime estimations using the coarse estimation and the zero-crossing based methods are evident. Although the 2 methods differ nearly by 10% to 20% depending on the battery technology, using a coarse estimation can yield to an optimistic prediction of battery lifetime based on cyclic ageing.

TABLE III
Cycle-life based on coarse estimation and zero-crossing (ZC) based micro-cycles estimation.

Technology	Cycle Life (coarse)	Cycle-life (ZCs)	Battery lifetime ZCs (yrs)
Lead Acid Gel	4.44E+03	4.04E+03	5.345
Lithium Ion	1.46E+04	1.19E+04	15.732

C. In the context of Solar Home Systems

In the context of Solar Home Systems, estimating the battery lifetime is a crucial exercise. As mentioned in Section I, it can be a vital SHS design parameter to be considered. This is especially true for the unelectrified BoP segments of the global population, where system costs along with reliability play a significant role in technology adoption. To justify the importance of estimating battery lifetime at the stage of SHS system design, this study was extended to investigate the impact of battery sizing on battery cycling and therefore on battery lifetime. The results of this investigation are captured in Figure 8.

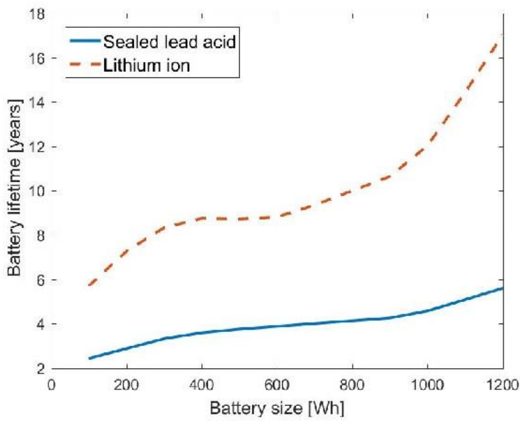


Fig. 8. Variation of battery lifetime as a function of storage size. A PV module size of 300 Wp was considered.

The battery size for the SHS application was varied between 100 Wh and 1200 Wh and the resulting battery lifetimes were estimated as shown in Section III-C. While the sealed acid battery can only seem to last from 2.4 years to 5.6 years depending on the battery storage size used in the system, the lithium ion battery can last from 5.7 years to 17 years, owing to an exponential dependency of the lifetime curve on DOD. It must be noted that not all battery sizes shown in Figure 8 can satisfy the load demand completely, i.e., the LLP will be > 0. However, this analysis has been done to highlight the effect of sizing on battery lifetime, and the graph by no means indicates the optimum battery size.

Figure 8 underlines the effect of battery sizing on battery lifetime. While increasing the battery size increases the upfront costs, it clearly has a positive impact on extending the battery lifetime, especially when considering Lithium ion batteries. This means that large upfront costs associated with $\$/kWh$ costs due to a large battery size could in principle compensate the battery replacement costs that otherwise recur during the SHS lifetime. This delicate trade-off needs to be further explored with respect to different technologies and cost factors. Therefore, battery sizing and technology choice is no longer a trivial selection when it comes to SHS design. In general, SHS designers are poised to gain from avoiding apriori choices related to sizing and technology, and instead estimating the battery lifetime based on intended application and predicted usage. The work described in this paper is an endeavour to provide one such methodology to reasonably estimate the battery lifetime.

D. Comparison with empirical battery lifetime estimation model

The accuracy of the lifetime estimation methodology described in this paper was compared to the results obtained from another empirical based lifetime estimation model based on Lithium Iron Phosphate ($LiFePO_4$) battery technology as described in [22]. To have a meaningful comparison, the zero-crossing based battery lifetime estimation model described in this paper was impemented using a ($LiFePO_4$) battery data obtained from a battery manufacturer [23]. The empirical model can been described by the Equations 6 and 7 [22].

$$cf = \sum_{i}^{E} \Big((k_{s1} SOC_{dev,i} . e^{k_{s2}.SOC_{avg,i}} + k_{s3}.e^{k_{s4}.SOC_{dev,i}}) \quad (6)$$

$$.e^{\left(-\frac{E_g}{R}\left(\frac{1}{T_i} - \frac{1}{T_{ref}}\right)\right)} \Big) Ah_i$$

Where cf is the capacity fading experienced by the battery due to all the cycling events, i is an event for an arbitrary length of time, Ah_i is the total charge processed during event i, E is the total number of events.

The temperature dependence term comes from the Arrhenius equation, where k_{s1} to k_{s4} are constants determined experimentally and reported in [22], $SOC_{dev,i}$ is the normalized standard deviation from SOC_{avg} in event i. This value is derived from Equation 7 below [22].

$$SOC_{dev} = \sqrt{\frac{3}{\Delta Ah_m} \int_{Ah_{m-1}}^{Ah_m} (SOC(Ah) - SOC_{avg})^2 . dAh} \quad (7)$$

Equation 6 was adapted to be used in the SHS application and the corresponding battery usage as described earlier in the paper. This resulted in an estimated capacity fading of 10.05 Wh, based on the empirical model for the SHS application with a $LiFePO_4$ battery. Consequently, the battery lifetime for the given battery size as used in the simulation was estimated. The values of the estimated battery lifetimes from both the approaches are tabulated in Table IV.

TABLE IV
BATTERY LIFETIME ESTIMATES OF $LiFePO_4$ TECHNOLOGY BASED ON EMPIRICAL AND ZCS-BASED MODEL.

Parameter	Empirical model	ZCs-based model
Battery lifetime (years)	22.89	23.77

As seen in Table IV, the empirical model and the zero-crossing based model estimate the battery lifetime for the same battery technology type and same application to be 22.89 year and 23.77 years respectively. In other words, the zero-crossing based lifetime model is giving a lifetime estimation within 3.85% of the empirical model obtained through battery experiments. Thus, it is shown that the simple battery lifetime model described in this paper can reasonably estimate the battery lifetimes when compared with an empirical model.

V. CONCLUSION

This paper described a simple methodology to quickly estimate the battery lifetime without needing before hand experimental or empirical data related to the electrochemical processes within the battery. Instead, this methodology relies on the intended application (load profile) and available battery data from the manufacturer for candidate battery technologies at hand for the desired SHS design. Relevant battery parameters like battery energy throughput, DOD, and active DOD through micro-cycle level data based on zero-crossings were extracted from the SHS simulation. The concept of active DOD was introduced and the difference between average DOD and average active DOD for the SHS application was highlighted. For a specific SHS system size chosen for the simulation, the methodology estimated a lifetime of 5.3 years for sealed lead-acid battery and 15.7 years for Lithium ion battery. The influence of battery sizing in an SHS on battery lifetime was also analyzed, showing that higher upfront costs due a large battery size could in principle be used to offset the replacement costs through SHS lifetime. The lifetime model was also compared with an empirical model based on $LiFePO_4$, and the lifetime estimates were found to be within 3.85% of each other. The authors hope that this simple yet effective method to estimate battery lifetime can be used by more SHS designers and practitioners in the field, across battery technologies and applications, provided reliable battery datasheets are available.

Recommendations and Future Work

Sufficient data needs to be known regarding the impact of temperature on battery lifetime, and a reasonable correlation needs to be derived between the combined effects of various battery parameters like C-rate, DOD, and temperature, and battery lifetime. Additionally, calendar fading needs to considered as well. Dynamic capacity fading needs to be taken into account within the simulation. In other words, the act of using the battery within a cycle already causes micro-degradation of the battery capacity. This needs to be captured during the simulations as well. Finally, this work needs to be extended to other battery technologies to get a comprehensive overview of performance of different battery technologies in SHS applications. Work is already under-way at the Delft University of Technology in this regard.

ACKNOWLEDGEMENT

This work is supported by a fellowship from the Delft Global Initiative of Delft University of Technology. The authors thank Soumya Bandyopadhyay, Vasilis Marioleas, Thomas den Heeten, and Yunhe Yu.

REFERENCES

[1] IEA, *World Energy Outlook 2016*, 1st ed. Organization for Economic Cooperation and Development, International Energy Agency, 2016.

[2] N. Narayan, J. Popovic, J.-C. Diehl, S. Silvester, P. Bauer, and M. Zeman, "Developing for developing nations: Exploring an affordable solar home system design," in *Global Humanitarian Technology Conference (GHTC), 2016*. IEEE, 2016, pp. 474–480.

[3] D. Palit and K. R. Bandyopadhyay, "Rural electricity access in south asia: Is grid extension the remedy? a critical review," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 1505–1515, 2016.

[4] T. Urmee, D. Harries, and A. Schlapfer, "Issues related to rural electrification using renewable energy in developing countries of asia and pacific," *Renewable Energy*, vol. 34, no. 2, pp. 354 – 357, 2009, renewable Energy for Sustainable Development in the Asia Pacific Region. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S096014810800205X

[5] G. S. Initiative, *Quality Charter: Quality Standards for Accredited Solar Suppliers*. Good Solar Initiative, 2016. [Online]. Available: http://www.goodsolarinitiative.org/uploads/2/4/8/5/24859908/good_solar_initiative_-_quality_charter_-_24mar2015_-_final_approved.pdf

[6] S. Mandelli, J. Barbieri, R. Mereu, and E. Colombo, "Off-grid systems for rural electrification in developing countries: Definitions, classification and a comprehensive literature review," *Renewable and Sustainable Energy Reviews*, vol. 58, pp. 1621–1646, 2016.

[7] A. A. Phadke, A. Jacobson, W. Y. Park, G. R. Lee, P. Alstone, and A. Khare, "Powering a home with just 25 watts of solar pv. super-efficient appliances can enable expanded off-grid energy service using small solar power systems," Lawrence Berkeley National Laboratory (LBNL), Berkeley, CA (United States), Tech. Rep., 2015.

[8] T. den Heeten, N. Narayan, J. Popovic, J.-C. Diehl, S. Silvester, P. Bauer, and M. Zeman, "Understanding the present and the future electricity needs: Consequences for design of future solar home systems for off-grid rural electrification," in *Proceedings of the 25th Domestic Use of Energy Conference, 2017*, 2017, pp. 8–15.

[9] M. R. Palacin and A. de Guibert, "Why do batteries fail?" *Science*, vol. 351, no. 6273, pp. 1253292–1253292, 2016. [Online]. Available: http://www.sciencemag.org/cgi/doi/10.1126/science.1253292

[10] P. Keil, S. F. Schuster, J. Wilhelm, J. Travi, A. Hauser, R. C. Karl, and A. Jossen, "Calendar Aging of Lithium-Ion Batteries," *Journal of The Electrochemical Society*, vol. 163, no. 9, pp. A1872–A1880, 2016. [Online]. Available: http://jes.ecsdl.org/lookup/doi/10.1149/2.0411609jes

[11] J. Wang, P. Liu, J. Hicks-Garner, E. Sherman, S. Soukiazian, M. Verbrugge, H. Tataria, J. Musser, and P. Finamore, "Cycle-life model for graphite-LiFePO4 cells," *Journal of Power Sources*, vol. 196, no. 8, pp. 3942–3948, 2011. [Online]. Available: http://dx.doi.org/10.1016/j.jpowsour.2010.11.134

[12] M. T. Lawder, P. W. C. Northrop, and V. R. Subramanian, "Model-Based SEI Layer Growth and Capacity Fade Analysis for EV and PHEV Batteries and Drive Cycles," *Journal of The Electrochemical Society*, vol. 161, no. 14, pp. A2099–A2108, 2014. [Online]. Available: http://jes.ecsdl.org/content/161/14/A2099.abstract

[13] P. Ruetschi, "Aging mechanisms and service life of lead-acid batteries," *Journal of Power Sources*, vol. 127, no. 1-2, pp. 33–44, 2004.

[14] M. Dubarry, B. Y. Liaw, M.-S. Chen, S.-S. Chyan, K.-C. Han, W.-T. Sie, and S.-H. Wu, "Identifying battery aging mechanisms in large format li ion cells," *Journal of Power Sources*, vol. 196, no. 7, pp. 3420 – 3425, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378775310012127

[15] "Installation , commissioning and operating instructions for valve-regulated stationary lead-acid batteries - solar battery data sheet," Hoppecke 2013, Germany, 2015.

[16] *Handbook for Gel-VRLA-Batteries, Part2: Installation, Commissioning and Operation*, EXIDE Technologies Industrial Energy, 10 2003.

[17] *Lithium-ion battery life, Solar photovoltaic (PV)-Energy Storage Systems (ESS)*, Saft, 5 2014.

[18] A. A. Phadke, A. Jacobson, W. Y. Park, G. R. Lee, P. Alstone, and A. Khare, "Powering a home with just 25 watts of solar pv. super-efficient appliances can enable expanded off-grid energy service using small solar power systems," Lawrence Berkeley National Laboratory (LBNL), Berkeley, CA (United States), Tech. Rep., 2015.

[19] Global LEAP, "The State of the Off-Grid Appliance Market," Tech. Rep., 2016. [Online]. Available: http://www.cleanenergyministerial.org/Portals/2/pdfs/Global_LEAP_The_State_of_the_Global_Off-Grid_Appliance_Market.pdf

[20] GIZ, *Photovoltaics for Productive Use Applications - A Catalogue of DC-Appliances*, 2016.

[21] Meteotest, "(software) meteonorm ver 7.1," 2014.

[22] L. Lam, "A practical circuitbased model for state of health estimation of liion battery cells in electric vehicles," Master's thesis, Delft University of Technology, August 2011.

[23] "Valence life — lithium ion phosphate battery manufacturer," (Date last accessed 2015-05-03, year=2017. [Online]. Available: https://www.valence.com/why-valence/long-lifecycle/