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Master thesis

“Benchmark analysis of lithium-ion batteries at different locations”

MSc. Renewable Energy

InnoEnergy

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Review

The present document aims to analyze different types of Lithium-ion (Li-ion) batteries and define which type is more suitable for a specific location, regarding the SOH (State of Health) value after one year of operation.

Three batteries have been chosen for this comparison, each one having a different performance according with mathematical models with different parameters. Two models are based in the Lithium Iron Phosphate ($LiFePO_4$) chemistry; with the difference that the Model 3 uses a carbon coated $LiFePO_4$. The model 2 is based on the Lithium Manganese Nickel Oxide ($LiNiMnCoO_2$, known as NMC) chemistry. These models were selected based on the existing studies available in the literature (many models have been developed for these types of Li-ion), and most importantly, the $LiFePO_4$ used to be the most used type of battery for electrical vehicles and nowadays the NMC is becoming the new trend. $LiFePO_4$ is used in many electric cars manufactured in China and NMC is a type used in very popular brands such as Tesla.

For each one of the models, the SOH calculation is presented and each equation is developed according with the temperatures at three different locations: Oslo, Norway; Barcelona, Spain and New Jersey in the US. For these places, the temperatures were considered and configured into the models. The trail period was a year, and as the temperatures were for the year 2016, the total cycle number was set to 366.

Results showed that the temperature plays a significant role in terms of the SOH rate of change per cycle. Even though the final SOH value is not significantly changing for the same model at different location, the set of values that the SOH takes is totally different. After analyzing the graphs obtained, a modification was followed in order to consider the real cases, where the mileage driven is not constant and is different at the three locations. Then a higher difference in the SOH was identified comparing each place.

At the end, a market analysis is presented in order to estimate the annualized cost at each place for each one of the three models. The cost-benefit is also a key indicator while making the decision of the most suitable battery.

It can be concluded that using a battery outside the optimal temperature value then can decrease its lifetime in the range of 1 to 3% only due to this variable.

Summary of contents

Glossary

Capacity fade. It accounts the amount of lost capacity in a battery considering the rated capacity as its initial value. Capacity fade is physically an effect due to ageing or working at a very low or very high temperature.

Depth of Discharge (DoD). It measures the amount of the charge that has been taken out from the battery, expressed in percentage. It value is 0% when the battery is fully charged and 100% when the battery is totally discharged.

PTC Heater. A Positive Temperature Coefficient heater is made from a ceramic material and has as a unique characteristic to ensure high heat transfer in small and tight spaces. It has the shape of a disc with many holes. The resistance in the disc is decreased, the temperature increased, so the air flow throughout the holes gets warmer and the space is therefore heated.

State of Health (SOH). It is an estimation of the general condition of a battery at any time along the lifecycle, compared with the new battery. It depends on many parameters, such as the remaining capacity, the resistance value, the self-discharge rate, the voltage, the rate of charge and discharge along the cycles and the charge acceptance; then it compares with the original value. Although there is no a unique equation, if a numerical value is estimated, it needs to account the number of cycles the battery has already worked.

State of Charge (SOC). It refers to the amount of charge available at the battery, so how much of the capacity of the battery is remaining. A SOC of 100% means a fully charged and a 0% represents a totally empty battery.

UDDS (Urban Dynamometer Driving Schedule). Defined by the Environmental Protection Agency (EPA), it is the representation of the city driving conditions. It is a pattern for the driving conditions in one trip for a light car. This trip lasts for 1369 seconds, and it registers at each instant the speed of the vehicle. As a pattern, it is used for estimating the distances by integrating the speed over the time. Therefore, it estimates the fuel economy, and in the case of electric vehicles, the driving range.

1. Preface

An electrical vehicle (EV) uses a Li-ion technology in most of the commercially available car models, since it is the most efficient and safe. The battery safety, availability of charging points close to the drivers and mileage range are important challenges in order to increase the market share of the EV in the upcoming years. Regarding the mileage range and safety, temperature is a key variable whose influence needs to be estimated in the most accurate way. Battery temperature will determine the performance along the lifecycle. Keeping the temperature in the optimal operation range will enhance longer distances for a longer time.

Many models available in the literature are focused in estimate the available battery energy in the battery while the car is running (named State of Charge, SOC), and in the other hand, in estimating the battery capacity compared with the rated capacity (named State of Health, SOH). The first one focuses in one cycle and the evolution of the value of some electrical variables along that cycle. The second one assumes a specific temperature and accounts the ageing effect after some cycles until it reaches the end of its useful life. Some other models run two batteries, each one at a temperature and compare the results.

However, temperature is different every year and also changes with the time of the day. A estimation of the battery performance or the battery remaining capacity should run the different cycles at different temperatures, since this change from one temperature to the other also influences the SOH value.

Using the models available in literature and experimental results, and leaving the temperature as a variable, will build and estimation of the ageing and temperature combined effect. If this is done for different locations, and local factors are also considered, the resulting benchmark is a useful tool in order to decide what kind of battery is the most suitable. Before choosing a model, chemistry of the battery, model where it is used, SOC variables and capacity have to be checked in order to make a close reality comparison.

2. Introduction

The actual context shows an increasing interest for including more energy sources in many countries around the world. Transportation, as a key category in order to enhance sustainability, is one of the main fields into consideration. The targets for this sector set in 2013 in CO_2 emissions for 2020 are 95 g of CO_2 per km for the European Union, 105 g for Japan, 117 in China and 121 in the United States [1].

Electric vehicles are fundamental in achieving a less pollutant transportation. There are many types of electrical vehicles (EV) but for this work the next ones belong to this category: Battery Electric Vehicles (BEV), Plug-in Hybrid Electric Vehicles (PHEV), Range Extended Electrical Vehicles (REEV), and Fuel Cell Electrical Vehicles (FCEV). In other words, EVs are the ones that get their power mainly from an electric motor, so therefore the Hybrid Electrical Vehicles (HEV) are not EV since they are powered mainly from a combustion engine.

Although the EVs were only 0.1% of the total vehicles in 2015, the last five years have witnessed a huge increase in the number of EVs. Particularly in Norway, the market share reached 23% and 10% in the Netherlands in the same year. In terms of cost, the batteries have experienced a drop of 75% from 2008 to 2015, and more policies have been addressed in terms of having rechargeable points along urban and rural areas [2, 3].

However, the main challenge is to increase the mileage driving range of the different car models. A target is to reach 300 km of range. Aligned with this, safety and reliability are main concerns in the industry. For the driver, it is important to know the mileage while driving in order to know when to visit a recharging point, and also if any maintenance is required. To monitor the battery performance in an EV in an accurate level is a priority for the manufacturers. A lot of research has been done in this field and many models have been developed to estimate the remaining charge and the available charge compared with the rated power.

For all the battery chemistries, temperature is key for their performance. As the Li-ion batteries are the used for EVs, Li-ion is the scope for this work. Therefore, the topic for this work is the temperature influence in the battery performance. Driving an EV at very high or very low temperature means a poorer performance. Depending on the specific chemistry, there is an optimal temperature range. When the car is driven outside this zone, degradation starts. EV performance in cold and hot temperatures is explained in this work.

A Battery Management System is the entity that controls the battery performance. Basically, BMS measures parameters such as temperature, voltage, current and capacity and checks that the values of these parameters are within an acceptable range. If the values are outside this range, it has mechanisms to regulate and avoid a significant damage, for example, heating up or cooling. Many of the opportunity areas of a BMS can be summarized in getting enough level of accuracy to get an optimal performance of a lithium-ion battery installed in an EV. In order to manage the battery, parameters need to be measured first. Therefore, a good BMS will keep a battery temperature with a short variation, will enhance as much as possible a uniform temperature distribution in all the cells, and will be light.

As mentioned before, there are available in the literature many models for estimating both the SOC and the SOH at a given temperature. But still there is a lack in the available models to verify the SOH if the temperature changes every cycle. If for a model the temperature is left as a variable and the number of cycles is a variable as well, estimation can be conducted.

For a specific place, if the degradation for both ageing and temperature are estimated, BMS can be designed in a better way to reach a longer lifecycle. A customized BMS for each place improves the performance. An improved performance will be reflected in a longer lifecycle and will also have a positive impact from the cost benefit perspective. For this work purposes, three different locations were chosen for this simulation. All the assumptions and important information is explained in detail.

Including the cost perspective for each one of the places and batteries will deliver at the end a very good benchmark analysis. For this economic comparison, the guidelines are also explained.

2.1. Objectives of the project

This work aims to enhance the following objectives:

- Describing the state of art of the Li-ion batteries and importance of the EVs.
- Analyzing the temperature influence in the battery performance and its importance for the Battery Management System (BMS).
- Estimating the State of Health (SOH) evolution in one year at three different locations, using the temperature values of those places. The SOH estimation is done using models where temperature has been left as a variable.

- Comparing the driving patterns and local conditions that may influence the convenience of purchasing one type or other.
- Making a cost comparison of the different batteries at the different places.

2.2. Scope of the project

After this introduction to the energy trends, the electrical vehicles (EVs), and a brief explanation of the market share of EVs across different locations, Chapter 4 refers to the Li-ion batteries, the different types and topologies, focusing in the ones used for EVs, the temperature difference in the different modules they are formed, as well as the charging and discharging process at different temperatures. The fifth chapter is dedicated to the BMS, its main features, and also important concepts in management for the batteries are presented, such as state of charge (SOC) and state of health (SOH). Also the main criteria in choosing a battery are pointed out.

In the Chapter 6, the problem to be analyzed is presented. Figures and data related with the poor performance at low temperatures and after specific cycles are explained for the chosen battery. Also, it is pointed out that there are several studies for the capacity reduction after a specific number of cycles, and about the performance at temperatures different from the optimal, but not that many about these both combined. Also, this chapter introduces important facts about the EVs main constraints in the countries where they are already been used to some extent, so the operation at extreme temperatures is proved to be one of the key issues.

In the same way, the structure of the exercise is presented. Basically, it is needed to define which type of battery is more suitable to be used in an EV depending on its location. The most suitable is defined as the battery that after one year of use (365 cycles) has decreased its capacity in the least amount (in other words, the one whose SOH is higher). For doing this, three locations are chosen, being Norway, the US and Spain. Based in the weather forecast, a monthly temperature average is estimated and then the battery is simulated to work under this condition (30 cycles at the given temperature). This is repeated along one year, considering the monthly average temperature. At the end of the twelve months the reduction of capacity is estimated (adding the reductions for each month). And then the state of health is compared for the three locations. In total, nine simulations will be conducted, three for each place, since three types of batteries are to be compared.

As it can be inferred, the most difficult part of the exercise is to calculate the reduction of capacity after cycles but at different temperatures. There are data about the reduction of this

capacity at a specific temperature, but for different temperatures, a correction needs to be set and checked for its accuracy. The formulas and input data for doing this are explained.

Chapter 7 presents the results and findings, including what is the period where the capacity reduction was the least, meaning this one is the optimal temperature, and comparing with the ideal temperature stated in the battery. Also it is defined from the three types of battery which one is the best for each location. Driving patterns are analyzed and also the economic side of the story is revealed by presenting an estimation of the annualized cost of having an EV in each one of the three locations.

The discussion of the results is the core of the Chapter 8. This one will include not only the accuracy analysis, but also how other important factors can be introduced to the model, for example, other atmospheric conditions, the environment where the charge is done, or if the car is used to travel for some days and then another temperature needs to be accounted in the model.

Chapter 9 lists all the conclusions and future scenarios that might occur in the upcoming years for the EVs. Also, what is the main learning from the model and whether this one is relevant or not for a better understanding of lithium ion batteries.

3. Li-ion batteries

A battery, by simple definition, is an energy vector. It makes possible to store energy and of course, the highest potential is with mobile applications and places where there is no immediate access to an electrical grid.

For this work, it is not one of the most important objectives to explain will high details the basics of a cell but to show the main drawbacks and constraints that the lithium battery has nowadays, specifically with the temperature variations.

As any other cell, Li-ion is formed with an anode, a cathode and an electrolyte. The main working principle is that the positive ions will flow throughout the electrolyte and the electrons will flow by an external circuit, therefore an electrical current can be taken. A set of cells arranged in different ways form a battery.

Lithium-ion batteries are very popular and have a considerable market share in the electronic devices such as laptops and mobiles [4]. One of the most important advantages of a lithium-ion battery is that it does not have a memory effect.

Within the battery available options, lithium-ion has the highest potential to store energy.

3.1. Topologies

A battery is a set of cells formed in a defined distribution depending on the power needs and the available space. Of course, the application plays an important role.

The most common topologies that are present in a Li-ion battery are depending also of the battery management system (BMS) and how complex it will be, therefore again the application is important [5]. If a more strict control is conducted, the topology will require more tools. The kind of cells (chemical components) is essential since the heat convection rate will be different.

The first topology is the distributed one, where the measurement, monitoring and the electronics used for balancing (getting that all the cells have the same voltage) are set in each cell, in other words, the controlling system us for every cell. The results are just sent to a master controller, but the control is done at each cell. Sometimes, manufacturers only offer to choose between distributed or non-distributed technology.

In the second one, several cells are managed by a slave control and then the results are sent

to the master controller. The master controller takes the data from the slaves and then the control actions are determined. This topology is called modular topology.

The third option is the centralized topology, where all the cells are connected to a master unit that after getting inputs from every cell defines the actions to take for balancing and therefore the control is done in one single place. But then wiring is needed at every place where a cell is and that increases the cost and complexity.

Topologies are also used in several fields, but the logic on the master and slave roles is basically the same. The next figure illustrates the topology for computational nodes. Distributed, modular and centralized topologies have the same meaning.

Figure 1. Different topologies for cell distribution. From left to right: distributed, centralized and modular. Source: COTS Journal [5] .

3.2. Types of Li-ion batteries

A brief review of the different Li-ion cells that form a battery is now presented in the next table. As a technical note, the lifecycle column refers to the number of cycles where the battery is useful, meaning with this that the capacity fade is less than 20%. Typically, manufacturers recommend replacing the battery when the capacity drops to 80% of the initial value [6].

Battery type	Application	Voltage level	Specific energy	Lifecycle
Lithium-cobalt (LCO)	Mobile phones, laptop	3.6 V (range 3-4.2 V)	150-200 Wh/kg	500-1000
Lithium-manganese (LMO)	EV, some power tools	3.8 V (range 3-4.2 V)	100-135 Wh/kg	500-1000
Lithium Iron	EVs, common to	3.3 V (range 2.5-	90-120 Wh/kg	1000-2000

Phosphate (LFP)	replace lead acid batteries	3.65 V)		
Lithium Nickel Manganese Cobalt Oxide (NMC)	EVs, e-bikes and other power trains	3.6 V (range 3-4.2 V)	140-180 Wh/kg	1000-2000
Lithium Nickel Cobalt Aluminum Oxide (NCA)	EVs (Tesla)	3.6 V (range 3-4.2 V)	200-260 Wh/kg	500
Lithium titanate (LTO)	UPS and solar powered street lighting, EVs	2.4 V (range 1.8-2.85 V)	70-80 Wh/kg	3000-7000

Table 1. Types of Li-ion batteries with commercial applications. Source: Battery University website [7].

As it can be concluded, most of the Li-ion are stick into a battery level between 3 and 4.2 V. One exception is Li-phosphate where the specific energy is less and also the self-discharge rate is higher. The graph below shows how almost all the types have higher energy density than other types of batteries.

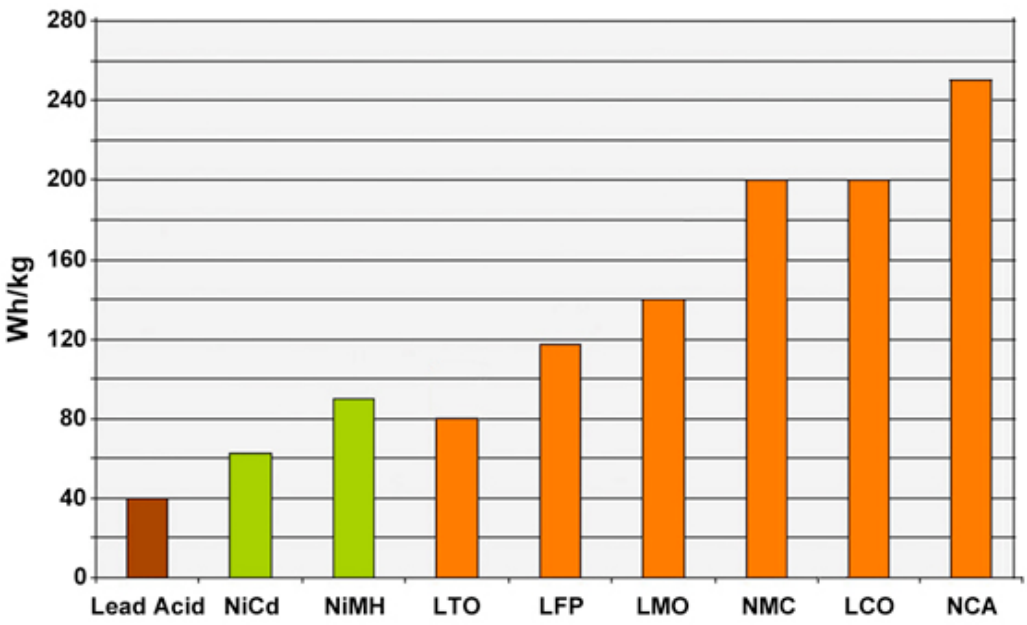


Figure 2. Comparison of specific energy of batteries. Source: Battery University website [7].

It is common to consider the lithium polymer as a different kind of battery. Some decades ago, the lithium polymer was a kind of battery whose main difference with the Li-ion is the use of a solid polymer as electrolyte. However, in order to operate, this cell needs to be heated until reach 60 °C in order to start conducting current. To solve this, the electrolyte was a gelled material. And many Li-ion are working with gelled electrolytes so there is no any difference between Li-ion and lithium polymer.

From the types described above, what is important in the scope of this work is to analyze Li-ion batteries with the highest range of temperature operation and with more capacity. The reason for this is the application to be analyzed: EVs.

Lithium titanate has the highest lifecycle, but the specific energy is not high enough. Decision is also based on the approach: looking for a substitute of the current batteries used in cars (lead acid) or batteries that work completely with EVs.

3.3. Lithium-ion batteries for electrical vehicles (EV)

As explained in the previous chapter, EV´s are not a new technology, and in many European countries, are becoming more popular. By 2015 in Norway, 23% of the vehicles were electric powered, whereas in the Netherlands the share was 10%. The US and China have in terms of units, the large number of EVs on the road, having more than 700 000 units combined [3].

Nowadays, the charge times, the cost and the places for charge and discharge are the main obstacles for the EVs market share among all the vehicles. Regarding the purposes of this work, an important indicator is the number of cells that are present in each car. Of course, to offer a bigger size of EV, the number of cells tends to be higher. The Mitsubishi iMIEV has 88 cells in 4 modules, Nissan Leaf has 192 cells and Tesla has 7616 cells. The number of cells in the Tesla allows it to get up to 90 kWh, however the consumption is higher due to the weight increases. Nissan Leaf is very light and the consumption is very low. In terms of the total distance that can be reached the winner is Tesla, since its model S85 can reach up to 360 km [4].

For the purposes of this work, three types of battery are analyzed, two of them based in the $LiFePO_4$ chemistry and one in the NMC.

$LiFePO_4$

This type of battery was the most used to replace lean acid types in cars. In the recent years,

Chinese car manufacturers (such a BY6) had this type of battery in most of the manufactured EVs. The reason for this is the level of safety it has because of the thermal stability. It can take high current rating and also has a long lifecycle, as mentioned before. As a drawback, it has low specific energy (3.2 V each cell, between 90 to 120 Wh/kg).

The thermal operation is described together with the model 1 features later on in this document.

NMC

NMC is the name given to Lithium Nickel Manganese Cobalt Oxide. It has been adopted recently for car manufacturers such as Tesla due to the fact its chemistry gives a very good performance. From nickel, it has high specific energy and from manganese gets a low resistance level. NMC batteries also have low self-heating rate, a main advantage when fast charging and ultra fast charging are used.

C-$LiFePO_4$

It was just mentioned that the normal LiFePO4 batteries have low specific energy and that causes low capacity. In order to overcome this issue, some methods refer to decrease the particle size (long particles have slow diffusion and that limits the power capability). Carbon coating is the most effective way since it increases the ionic conductivity and the capacity reaches up to 90% of the theoretical capacity for a cell with this cathode, according with Yamada and Hinokuma (2001) [7]. Also the capacity fade is not as high as in the normal LiFePO4 after each cycle, so the lifetime is increased.

3.4. Electrical equivalent circuit

As the aim of this work is to find out as much as possible about the temperature influence, a useful way to approach it is with the electrical circuit. By definition, a battery is a voltage source with an internal resistance. Depending on the complexity level, more impedances are added, since more physical phenomena are taken into account, like the hysteresis, as stated by Rahmoun and Biechl (2011) [8].

There are mainly three electrical circuits that represent a battery, depending on the effects that need to be considered. The first one is the Internal Resistance model (IR), which only shows a voltage source with a resistance. Then the One Time Constant (OTC) model adds a RC branch; this branch is to account the transients in each cycle (being a cycle a charging and discharging process). And the third one, the Two Times Constant (TTC) model adds

another RC branch that represents the long term effects in the battery, being mainly the diffusion effect. A scheme of the three circuits is presented below. Later on, the third circuit is used as a basis for one of the models at the benchmark process.

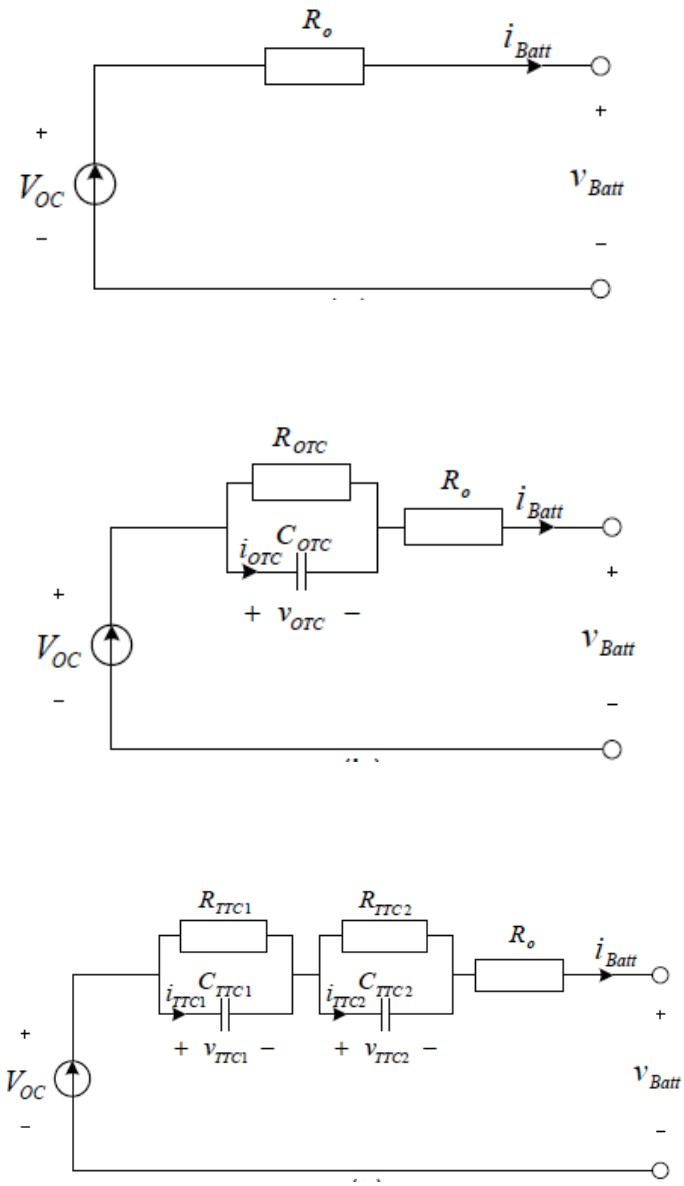


Figure 3. Electrical equivalent circuit for a battery, based on the complexity level, presented by Rahmoun and Biechl [8].

3.5. Charge and discharge process of a Li-ion battery

The charging and discharging process has been described with many models and

experimental data. In all these previous studies, there is a pattern for Li-ion batteries: the charging and discharging takes place in a quite stable voltage level most of the time, but at the beginning and at the end of this process, the voltage changes in a very steep way. The curve of charge/discharge will have a form like the figure shown below, which show a performance of a LiFePO4 with a capacity of 16.4 Ah, at 3C rate and from 30 to 80% SOC.

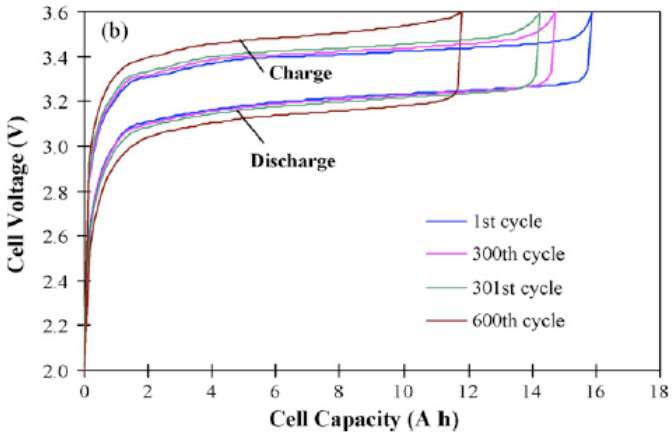


Figure 4. Charge and discharge process for a typical LiFePO4 cell at a constant temperature of 50 °C [9].

In spite of the fact that the curve will have that shape in the cycle, many factors play a role in the steepness and the levels that the curve will reach. These factors are:

1. Rate of charge/discharge. For an electrical vehicle, the charging process needs to be fast enough in order to make it commercially viable. The discharging is in function of the driving pattern and also the chemistry of the battery. At the available literature, the rate and discharge speed is measured according with the battery capacity. The charging and discharging rate is described then as 1C, 2C, 3C, etc. The C represents the value of the current that will make the battery to be charged in 1 time (1 hour). For a battery of 3 Ah, 1C is 3 A. And then 2C is 6 A. Then the C current value is specific for a battery [7].

   A common drawback for the EVs development is that the high-speed charges are a demand from the users, but will have the effect of reducing the battery lifetime. This is mainly due to the increase of temperature that the fast charging has, so the degradation increases. A higher charge rate means that the temperature is increasing; a higher voltage and current levels will be reached. One of the solutions for this is to charge only up the 80% of the rated capacity when doing a fast charging, to avoid the high voltage. And during the discharging process, again, it is important to avoid a fully discharge since that represents a higher degradation. When the battery

is discharged until very low levels, then part of the copper in the anode dissolves in the electrolyte, becomes an ion (this is actually degradation) and causes dendrites when the battery is charged again. If the dendrites are very high, a short circuit will occur. In most of the cases, the Li ion batteries have a SOC operation range that goes from 25% to 85%. For EVs, in most cases the charge and discharge occur between 30 and 70%.

Even though it is not the scope of this work, the rate of charge and discharge is clearly playing an important role in the models presented to be compared. In the equations for each one of the models, the rate of charge and discharge clearly influences the results. The degradation of the battery, meaning with that the capacity reduction or de reduction in the SOH value, is proportional to the rate of charge and discharge.

2. Ageing. The relationship for this variable is quite clear: as the battery gets older, the capacity is reduced and then the voltage levels reached make a smaller range. Also, as the number of cycles increases, the capacity fade is higher and that also modifies the shape of the curve. The magnitude of these changes depends on the model used. This was quantified in this work and is explained in the results chapter.

3. Depth of Discharge (DoD). The relationship of this variable is quite obvious since the maximum and minimum voltages that are reached are the upper and lower values for the curve.

Also the DoD is important since given a model, the operation at each cycle needs to be set in a specific range for a cycle. It's important that the battery is not being plugged to a power source after it is fully charged and also that the total available power is delivered until the battery is empty. A common practice is to keep the Li ion battery at a minimum level of 20%, however there is no a established and exact standard on that. If the battery is completely discharged, the lifecycle is reduced significantly. And this is related to the DoD value. The higher the DoD value, the lower the lifecycle. For a NMC and a $LiFePO_4$, the 100% DoD means that the battery will only last between 300 and 600 cycles, whereas for a 60% DoD the range is between 600 and 1500. If the DoD is only 10%, the range is between 10000 and 15000. Confirming this, information about Panasonic cells refers that if the DoD is 10%, the lifecycle is 4000, but if is 80%, the lifecycle will be only 550 [4,10] .

4. Temperature. Temperature of the cells rules the performance. The optimal performance of the cells is achieved if they work within a temperature range. When

this does not happen, the capacity is reduced and then the curve changes its shape. For very low temperatures, and depending on the battery chemistry, the cells need to be heated up. At very high temperatures, the degradation starts and also the power supplied by the battery is limited. The exact temperatures for this depend on the chosen model. A detailed analysis of the temperature of the cells and its effect in the performance is explained later on.

It is precisely the temperature the variable accounted as the key in evaluating the SOH. Basically, the temperature degradation means less power because of the voltage drop in the battery increases (voltage drop that account losses in the electrical circuit). In terms of one single cycle, capacity will change according with the temperature, but then if the second cycle is carried on in an environment with a different temperature, the capacity will change although the maximum capacity at ideal temperature will be almost the same. As the battery gets older, the potential maximum capacity (the rated capacity in the first cycle) is reduced in part because the cycles are being conducted at temperatures lower or higher than the ideal temperature. Another reason is of course the normal chemical wear from the cathode and anode, and of course, the evolution of the resistance.

3.6. Temperature effect: developed battery models

There are several theoretical and experimental models in the current literature that estimate the performance and lifecycle reduction due to the temperature difference with the optimal operational value.

The models are also conducted when the conditions are not optimal at all just to figure out the operation limits (for the case of Li-ion batteries, at very high and low temperature, after several cycles, with very low or high voltage, etc.). And this work will focus in the temperature analysis.

Temperature analysis is not only focused in the battery as one single entity. Also the cells that form the battery are the target. Temperature differences are present along the different cells depending on their position.

As it can be inferred, for a battery, the number of cells is high so therefore the number of possible arrays increases, and there is, at least from a theoretical point of view, a higher level of freedom to reduce the temperature difference among the cells inside the battery. As the power needed is bigger, it is possible to refer to different set of cells within a same battery

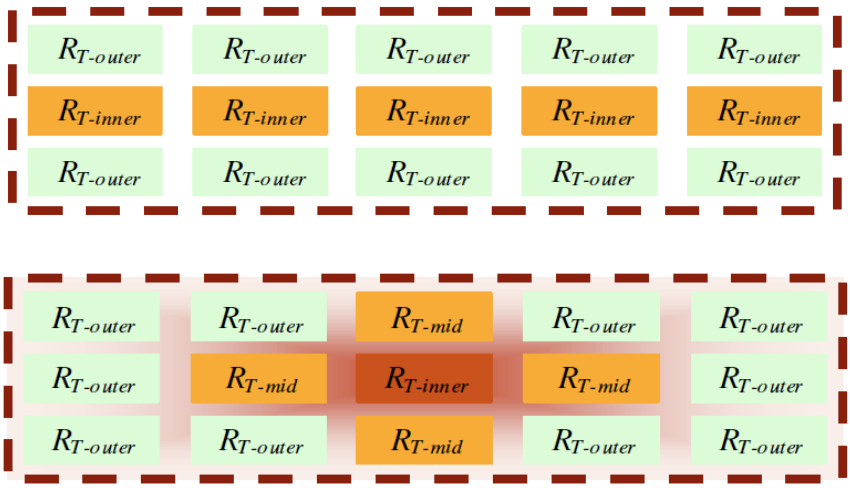
(modules or groups of cells).

Due to the reason that the battery requires a single value of temperature in a simplified model, one of the most frequently done assumptions is to take the average temperature of the cells. In order to reflect the reality as much as possible, the optimal array is one where the temperature differences are as less as possible. By doing this, another benefit is to avoid one of the cell reaches a very high temperature-or a very low one- and the balancing is needed in many less situations. As explained in the next chapter, balancing can be a very complex process and if the differences between the temperature (and therefore voltage) are very high, the situation is less from ideal.

In summary, an optimal array means a well designed BMS. In general, the first approach is to define the complexity level in the heat transfer analysis inside the battery. For sure, the cells that are surrounded by other cells only and are at the center will have a high temperature. The cells at the extremes will have a higher convection rate and lower temperature.

Inside the battery, the cells are completely enclosed, then convection through air flow is not an issue (if gases are produced they will not flow), however, natural convection is still produced among the cells.

Huria (2015) proposed three basic approaches for temperature differences in the cells, with a battery of three rows and five columns [5]. These models are presented below.



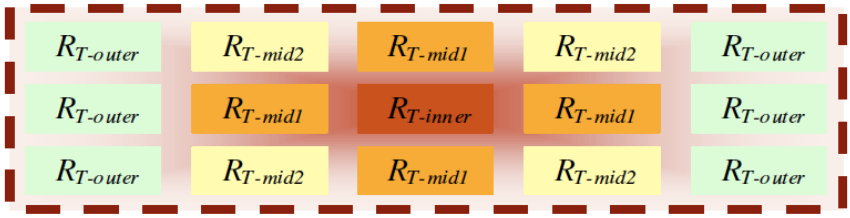


Figure 5. Different temperature levels for a battery with 15 cells [5].

The first one considers only two temperature levels, one in the inner cells and another in the cells at the boundaries of the battery. The second one includes the assumption that the cell at the center has the highest temperature and the four cells that surround it are the next in heat level, so three levels are managed. And at the third one, another temperature level is set so the cells that surround the center but are not direct neighbors have different thermal energy level.

When the application is an electrical vehicle, because of the design and space where the battery is, in order to avoid the battery gets at a very high temperature or the temperature distribution is altered, cooling methods are applied. This cooling can be conducted in three different ways, as presented by Muratori (2015): with air, with water/glycol or with a refrigerant. The way this cooling works is analog to another cooling system.

3.7. Charging and discharging at low and high temperatures

The aim of interest is the charging and discharging at low and high temperatures, meaning ambient temperatures. The influence of extreme temperatures is explained in the following lines.

Temperature is essential in battery performance. As any thermo chemical process, battery charging and discharging is optimal at a certain temperature. In an environment where temperatures are too high or too low, the performance is drastically affected, and outside the operational range, the battery will not work.

One of the main constraints for all kind of Li-ion batteries is that charging is impossible at freezing temperatures, however discharging might be still done but with a low performance. Even if charging and discharging is technically possible at temperatures very close to the theoretical limits, the performance and lifetime are affected.

Lithium batteries are a suitable option for EVs. However, the main constraint for their implementation and to get a higher share of the market is the high cost they have compared

with other batteries and with other energy sources. Part of the cost difference that is present in an EV is due to the complexity of the attached battery management system (BMS), needed not only to avoid a complete discharge but also to ensure an acceptable operation level.

In terms of operation, EVs need to be within ideal range. As previously mentioned, when the temperature is really low, the resistance increases, the capacity that can be delivered is lower and that means a less mileage range. It can be also the case that the battery cannot start working when the temperature reaches very low levels and then the BMS needs to heat the battery up. Normally Li-ion batteries cannot be charged below zero Celsius degrees, although they can be discharged at temperatures below that. A risk is then that while driving at freezing temperatures, the battery gets completely discharged (considering that the performance is reduced due to the same fact) and there is no possibility to charge it, if the car is not located at the charging point.

Then the question is until what extend this represents an issue, how much is the temperature affecting in the performance? To have a reference, the National Renewable Energy Laboratories (NREL) from the US developed some trials [11]. First, when the temperature is very low, the capacity is reduced in different ways, being a constant that the lower the temperature, the drop is more considerable: when there is -10 °C, the capacity is only 85-90% of the original, and when there is -20 °C, it drops to 60% (again, the battery cannot be charged at this temperature but can be discharged), also in this range the value of the resistance is duplicated. Regarding the operation at high temperatures, the power lost increases as the temperature is higher, but in a less extend, meaning with this that the performance at high temperatures is not as harmful as with cold temperatures. The experiment showed that in Minneapolis, with a mean temperature of 8 °C, had a 25% power decrease in 15 years, whereas Houston, with 20 °C on average, had a power decrease of 43%. Conclusion from this experiment is of course, to oversize the battery if the car is being used in hot climates.

The NREL defined a desired operating temperature range for Li-ion batteries; within this range the battery delivers the rated power. At the low temperature side, the resistance is higher so the battery is more reluctant to supply the power, and at the high temperature side the degradation limits the power. Besides of the reduced power from being outside this comfort zone for the battery, operation at cold or hot temperatures leads to a capacity lost that is not recovered anymore. If degradation starts, is a permanent loss. And to account the magnitude of this loss is one of the objectives of this work. In addition to this, one of the most important tasks of a BMS is the thermal system, that is on charge of heating up the battery when temperature is below the freezing point and protecting from overheat.

A big constraint for the EVs is that operating at freezing temperatures means a reduction not only for operating outside the optimal range, but also for the heat needed to the cabin. In a fuel car the exhaust heat provided by the fuel consumption is used for heating the cabin. For the EV case, the energy needed needs to come from the battery. An electric heater is installed for being used for the cabin. The Technical Research Center for Finland (VTT) estimated that the reduction in capacity due to the needs of the cabin takes at the end more energy than the driving energy. As a reference,a test in Helsinki gave as a result that the normal driving energy taken is 0.116 kWh/km, if the battery is put in an environment where the temperature is -20 C, the energy is 0.118/km. This means a reduction in the driving range from 130 to 96 km. Then the energy taken for the PTC heater (of 4.5 kW) is 0.236 kWh/km. Conclusion is that theoretically the energy for heating is higher than the energy for driving. And then with the heater the range drops until 32 km. The range drop caused by operating at a lower temperature and heating the cabin is 67% [11].

Cabin heating estimation would represent the worst case, since the temperature will change. The PTC will change the power depending on the temperature, so it will not operate at full power all the time.

The most important conclusion from the temperature analysis is to set the factors that modify the battery operation temperature in the driving. The cold battery condition is consequence of the outdoor temperature only, whereas a hot battery can be possible due to a hot environment, a very fast charging or if the driving is at a high speed (since it demands high current).

4. Battery Management System (BMS)

In any battery, a Battery Management System (BMS) is key for safety and performance. As it can be inferred from its name, a BMS will be on charge of enhancing an acceptable working life based on measurement and optimization. It is, in just one phrase, the control system of the battery. Therefore, it will be on charge of verify that the battery works in a proper way.

As a battery manager entity, the first task of a BMS is to measure the performance of the battery, so the need of control can be evaluated. Then, if control measurements are needed, mechanisms take place and the battery is kept safe.

Operation of a cell is basically charge and discharge. As mentioned in the beginning, the lithium battery is an energy vector, so it stores energy for any use. When discharging, energy is given to another device. This operation need to be conducted in what is known in the literature as the safe operative zone, meaning this within a defined range of voltage, current and temperature.

The second task of a BMS is to manage the battery, based on the measurements previously conducted and the defined limits. The most important is to keep the battery protected, so it does not represent a risk (i.e. a risk for the driver in an EV). The protection is carried basically throughout avoiding the cell is undercharged or overcharged outside the limits. Then, the variables to be controlled are the voltage and the current. If the battery is overcharged, then temperature increases and chemical reactions will cause the temperature to increase even more. The main idea of the control is to keep the voltage within the limits so the temperature is kept also in safe values.

For the chosen case study, application of lithium ion battery in an EV, temperature influence is critical. Temperature increases when the battery is charged. But the influence of temperature can be analyzed the other way around. For cold temperatures, the discharge will be faster. If it is a self-discharge, the discharge is faster at higher temperatures, as demonstrated by Zhang and Quan experiments (2015) [12].

Management is also related with balancing the cells inside a battery. Even if realized with high precision manufacturing, the cells will not be completely uniform, so it is a undesired but real effect that the charge is not at the same rate. A BMS typical control measurement is to stop the charge if one cell reaches the maximum voltage limit for protection, and then release the excess energy to have all of the cells at the same charge. In the same way, in the discharging process, if one of the cells reaches the lowest allowed level, the other cells need

to equilibrate. Therefore, balancing can be passive or active. If passive, the excess energy in the cells is released only. If active, the energy that is released from one cell with higher level of charge can be given to other one with lower level. There are many algorithms related with active distribution, with different levels of complexity.

The objective of this chapter is to state the importance of a thermal BMS in the system regarding the thermal characteristics.

This cell management, if done properly, will ensure that the cell is operating inside the safe zone. It is possible to define if the operating way is optimal or not based on the ideal temperature for that type of cell. Once it is ensured that battery is in the safety zone, charging and discharging need to be evaluated. For the particular example of an EV, knowing the charge at any time is crucial to calculate the distance the car will run without needing to be charged again.

There a few terms that are very well known in the current literature and are essential to understand whether the BMS is being successful or not.

The state of charge (SOC) is a parameter that indicates how full the battery is. At a fully charged battery, the SOC is 100%. The complimentary of the SOC is the depth of discharge (DoD), that is 0 when the battery is fully charged and 100 when the battery is empty.

The last two indicators are useful in the day to day performance. However, due to the decrease in performance of the lithium ion battery with the time, a BMS also needs to consider how good is the performance compared with the performance at the beginning of its lifetime, therefore measuring the SOH.

Related with SOC and SOH, the cell capacity (extractable charge) is an important variable that changes with the lifetime (lifetime is given with the number of charges and discharges processes and the level of charge/discharge cycle). Another commonly used way to evaluate the cell performance is the cell efficiency factor.

Both the SOC and the SOH cannot be directly measured as other parameters like the voltage. The measured data are used then to estimate the value of the SOC. Different algorithms and methodologies can be applied depending on the accuracy level and the application. In the next chapter the most common algorithms related with estimation of SOC and suitable for EVs are presented.

The fourth task of the BMS is the communication and data processing for display. As the BMS can be seen as a control system, with the input data from the cells, the output is a set

of data that are an input as well for other devices. Even for testing the BMS needs to display in an external device the evaluation results in order to be aware of the state of the battery. It is necessary to define if the BMS will send the data when plugged in with a cable or with another solution such as Wi-Fi or Bluetooth.

The following diagram shows the tasks that are conducted throughout a BMS.

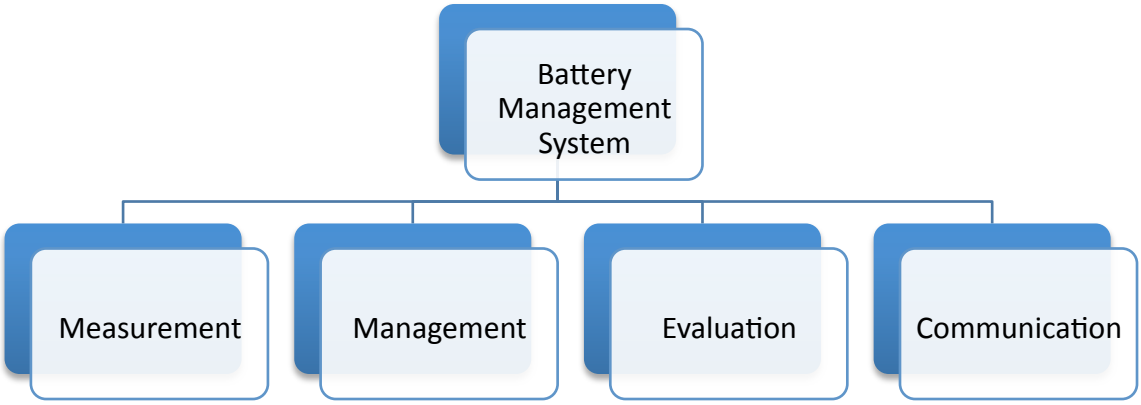


Figure 6. Battery Management System (BMS) main taks.

Now that the most important considerations have been explained related with BMS, the focus is to consider a BMS for and EV. And for this work the key variable is the temperature.

The type of BMS to be used is chosen based in the application, but also in other parameters that are explained below.

4.1. Components of a BMS

Application

The aim is to improve the accuracy in extreme temperatures in a vehicle, but still it is needed to specify whether the car will be hybrid or completely electric.

Inside the application field, manufacturers ask to define if the car will have a particular use such as military or will be in touch with water. If is a traditional car for urban use, here is

where the weather plays a role, together with other relevant information (i.e. the average speed of the car according with traffic issues). And also, once it is defined that the interest is an EV, then the dimensions of the car need to be taken into account.

Battery shape

As the size is defined, then the specifications of the battery can be analyzed (excessive or lack of space are undesirable). There are mainly four arrays of the cells inside a battery: small and large cylindrical, pouch and prismatic.

Type of battery

The type of battery is defined by the voltage needed for the selected application. There are different types of lithium battery, so for example LiFePO4 will be for a 3.6 V of maximum voltage, whereas for 4.2 V LiPO will be the option.

It is possible, based on the dimensions of the available space, to define the number of cells in series, the number of battery sections and the maximum current that will be supported.

Technology

The choice can be analog or digital, depending on the needs. From the optimal perspective, a referring to electrical vehicles, the best option will be digital technology.

BMS

Several variables need to be defined and related with the BMS. The first one is the topology of the cells inside the battery.

After the topology, the accuracy level is defined based in the cost and the type of cell. Of course, first the estimation of the operating values is conducted so a good estimation is referred. The most important accuracy to be got is the voltage, together with the voltage measurement rate. Additionally, current can be measured as well and if required, as in the chosen case study, temperature is part of the sensing package.

The next one is the SOC balancing. It is possible for the manufacturer to set the balancing point at different parts of the cell. Of course, it is needed to choose the algorithm and the amount of current use to balance. And the most important decision is whether the BMS will apply a passive or active balancing method. This is a decision influenced besides of the cost, by the application and then the level of complexity it is wanted to deal with. It is even possible to estimate or not the SOH (for display purposes) [13].

Interface

Depending on the desired parameters to show, the interface may differ from one model to another. It is possible to include or delete warnings, and include drivers and compatibility with other components of the device. More importantly, the data measured with the BMS need to be transmitted and processed, like any other data, so definition of the hardware ports is also crucial.

External case

For a battery where temperature and control are really important, the case materials and connectors quality need to be guaranteed. In general, the materials for the external closure available are metal and plastic.

4.2. Thermal control in a BMS

According with the NREL guidelines, the BMS has to keep the battery temperature within a range of 15°C to 35 °C (defined as the optimal performance range). Also, in terms of temperature, the BMS should keep the temperature among the cells as uniform as possible, being the limit between the hottest and the coldest of 3-4 °C.

Two considerations of thermal management are important for this work: the thermal control method and the considerations to reduce the temperature effects in the long term.

Regarding the thermal control, there are mainly two methods: thermal control with air and thermal control with liquid. In the first case, the air is used either for heating or cooling, being the simplest case just letting outside air in, and if more complex a heater and evaporator is used. The advantages are that is low cost, avoid all the complexities of incorporating a fluid, in the case of cooling relies on all the heat will be out and the maintenance is not very difficult. However, the temperature of the battery will not be uniform and also it is in all cases combined with the cabin thermal control, a fact that represents a drawback in many cases.

If the thermal control is conducted with a liquid, then the temperature profile is more uniform, since the liquid is wrapping the battery case. Normally the working fluid that controls the battery temperature is in closed loop and throughout a heat exchanger the heat is added or exhausted to the surrounding. Of course, the size is less and the temperature control is more effective since the fluid is a good heat conductor, however, is heavier, costly and in case of failure may lead into a leakage.

Based in the cost, the thermal control in the batteries is in order of increasing cost: the air

cooling system, the small vapor compression system, vapor compression and phase change material. The experiments run by the NREL showed that the capacity loss is much lower with the vapor compression system, since registered between 5 to 10% reduction in three locations: Phoenix, Houston and Minneapolis [11].

At cold weather regions, a third option is thermal management throughout electrical grid, that is having a heater resistance and using it to heat up the fluid that controls the battery temperature. If this is done before driving it is called preheating. This is done also for hybrids, but in the case of EVs, the capacity loss reduction reaches 7.1%. The main drawback in this case is that the circuit can simultaneously charge the battery and do the preheating. And of course, if the preheating needs to be done in the outdoor cold environment, part of the capacity needs to be used on doing this.

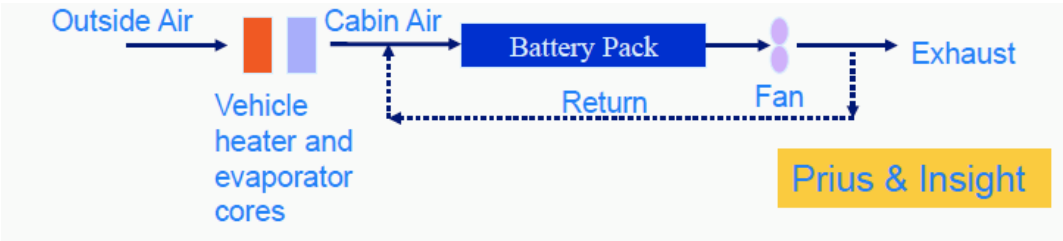


Figure 7. Thermal control system with air as working fluid. Source: NREL[11].

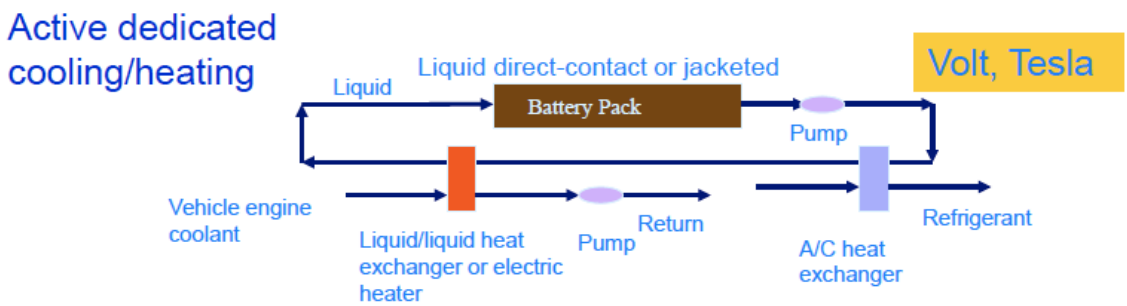


Figure 8. Thermal control system with a liquid as working fluid. Source: NREL[11].

5. Benchmark analysis guidelines

This chapter presents all the assumptions, initial data to be used and the model structure for the work.

Three battery models are to be compared in three different places. So these three batteries are installed in an EV and used for one year. And they are compared based on the remaining capacity. The one with more capacity is then the most suitable. And this is done for three locations, so at the end there is an optimal battery model for each location.

In this chapter, the first part is focused on the battery model important parameters to account for the benchmark to be conducted. From the analysis of current models available in literature, one set of equations will be developed specifically for this case. There are several models that incorporate the temperature of the battery with the SOC (what temperature will be reached if the charging is conducted at ambient temperature). And there are several models about the SOH depending on the number of cycles. So a link is needed between these two parameters. Basically this link is expanding the SOH number of cycles at different temperatures. Therefore, instead of having one trend, there will be more. It is known that the speed of charging influences the temperature that the cell reaches in every cycle, so this parameter is also considered.

The second part will explain the important information regarding the places, being this information about weather conditions and use of vehicles. Also, how the charging process is conducted, what is the average mileage, if there is any harsh condition besides the temperature level, and if the number of cycles can be assumed to be the same as the number of days of the year. Additionally, what is the most common type of battery used there and what are the main reasons for that.

In total 9 cases are presented, three batteries located in three different places. And for each case there is as input a temperature value for every day 366 times. After estimating the temperature of the cell and the temperature of the battery, the reduction in the SOH is estimated for the cycle of that day. This reduction is different based on the temperature value that changes every month. But also other external parameters are analyzed to realize whether these ones play a role and if they do, up to what extend and defining if this can be estimated or not.

Once the SOH value is known at a specific time, the mileage range can be estimated if the driving pattern is known. In the model 3 the SOH is also estimated based in the mileage

range, as it will be explained. The driving pattern shows the velocity and the time the car was running at that speed, on average, depending on the location.

The Environmental Protection Agency of the US (EPA) has developed a chassis Dynamometer Driving Schedule (DDS) to calculate the emissions and the fuel economy [14]. This is a standardized driving cycle, a plot that represents speed and time. So the car is run under different conditions (urban, highway, cold temperature), and the speed is measured every second. The trial settings are defined by the conditions, and in the case of the EPA one, it is a standard. Once this trial period is concluded, the result is a graph with the different speeds along the time. The pattern for the EPA that is followed in this work is the Urban Dynamometer Driving Cycle (UDDS), a representation of the urban driving conditions. A test is defined by 7.45 miles (11.987 km) along 1369 seconds.

The procedure for calculating the mileage distance for a particular battery is to define the SOC levels that represent one cycle (i.e. from 80 to 30%) and measuring the power profile under the UDSS. In other words, to run the battery at the speed conditions given by the UDDS under the SOC limits. Then the distance is calculated integrating the time taken and the velocity curve that is got. Before the integration, it is important to consider that the power curve complies the power curve correspondent to the speed curve. It is logic to infer that the more cycles the battery has, the mileage range is reduced. Depending on the battery chemistry, the total time span will change and therefore the distance. Also the temperature will modify this span, being more significant this reduction at low temperatures. It is possible that at very low temperatures the resistance increases up to a level that the voltage is too low for operating, then after that time the battery needs to be heated up.

The UDDS represents the urban conditions suitable for a typical city in America. There are different schedules available. EPA developed a special schedule for New York City and for highways. In Europe, a schedule was developed by the Economic Commission for Europe (held by the United Nations). In Japan, the driving schedule pattern is regulated by the Japanese Industrial Safety and Health Association; in this case, the 10 and 15 model apply. For each one of the models chosen, the driving schedule is specified [15].

5.1. Battery models

From the available literature, information about the battery performance modeling was analyzed and based on these findings; the algorithm and equations were used. For each particular case, all the assumptions and considerations are explained.

At the available literature, many experiments focus in the $LiFePO_4$ battery. For this work, two

models of this type were chosen as they are used in the popular brand BY6 (a Chinese manufacturer of EVs). The other battery type is a NMC, used in commercial brands as Tesla. However, the specific model used in a Tesla is an upgraded version of the model used in this work (models for this new type are still under development).

Battery model 1

The first battery model was developed by Qing, Huang and Sun (2014) [16]. Their work was focused in determining the battery capacity attenuation rate, Cr. So the SOH can be defined then as the difference with that parameter.

The Cr equation is based in the Arrhenius model, and the damage cumulative model. The equation got in this work is eq. (1)

$$C_r = mN^n \qquad (1)$$

And then the experiment and the results were analyzed in order to get the values for the m and n. This experiment was carried on with a battery of $LiFePO_4$ of 4.8 Ah each cell and a voltage level between 3 and 4.95 V. As the cells are connected in parallel, the voltage range is the same. Even if the experiment is conducted with single cells (multiple cells are used of course, as the series of experiments is very large), and the degradation level will happen along the cells if put in the same battery. The experiments were conducted with NBT tests systems and according with the New European Driving Cycle (which is a tool that represents the driving conditions in Europe for urban sites, on average). Following this driving cycle, it is recommended to have 5°C and 10 °C for charging and 10°C or 20°C to discharge (on that range), as well as 30 minutes of resting time between charge and discharge.

Once the data were analyzed, the variation of m and n values was pondered based on the influence of current charge and discharge and temperature mainly. At the beginning the charging and discharging process were counted as separated, but it is possible to combine them as presented in the final equation estimated. And finally the temperature effect was put into equation (2).

$$C_r = 0.01656 I_{ch}^{0.3428} I_{disch}^{0.3428} \left[e^{\frac{942.67}{T}} N^{14.2351 I_{ch}^{0.1995} I_{disch}^{0.0237} e^{\frac{135363}{T}}} \right] \qquad (2)$$

As key findings, Cr reaches the lowest value at 30°C, as the temperature goes up or down Cr is higher. Also, the attenuation rate is higher when charging compared with the one at discharging. The accuracy of this equation was 95% in that work.

Even though this model works very well in terms of accuracy level, after the 254th cycle, the equation is not fitting. Mathematically, it is following a parable and after that cyle the SOH is growing again. Therefore, an alternative should be found. A first option was to calculate a growth factor, based on the performance that the battery has at 25°C, so after the 254 cycles, the ageing can be assumed to be constant and equal to the last degradation rate, so from that point the trend will be linear. This can be assumed as a provisional solution, but has no clear basis. Then another model needs to be used in order to conduct the test along the 366 days. And this additional model should be also based in the degradation rate.

Wang developed a model that fulfills these requirements in 2011 [17]. In this work, the degradation is assumed as capacity loss and is related with the temperature and the rated capacity, as well as the cycle that is taking place. The equation has a very high accuracy level, however, compared with the model that was explained before, the current charge is not taken into account, and then a good solution consists on using this model after the 254 cycles have been completed. Before doing this, equation 3 was set into the model and results checked in order to find if the models are related one to each other.

The equation (3) proposed by Wang is:

$$Q_{loss} = B \cdot e^{\frac{-Ea}{RT}} \left(A_h\right)^z \qquad (3)$$

Qloss is the capacity lost in percentage, B is the exponential factor, T is the temperature in Kevin, R is the gas constant (used in the ideal gas equation), Ea is the activation energy Ah is defined as in the equation (4):

$$A_h = (cycle\_number) \times (DoD) \times (full\_cell\_capacity) \qquad (4)$$

Battery model 2

The second model was presented by Zhen, Fu, Xu and Wong (2013) [18]. That team conducted a series of experiments with Li-ion batteries for EV and with a voltage range of 3 to 4.05 V. The initial capacity of the battery was 32 Ah. Aligned with the SOH definition, when the capacity is only 80% the battery needs to be replaced. Also, in this particular case, the minimum capacity is 23 Ah.

The followed approach in that work was the genetic algorithm, where basically the population evolves towards an optimal solution.

The used circuit was the resistance-capacitance model. As known, the battery consist in a voltage source together with a resistance in series (to consider the losses in charging/discharging, or in other words, the battery has an internal resistance when charged and discharged) and a pair of elements connected in parallel: a resistor and a capacitor. This branch represents the diffusion effect. And for this case a couple of elements was added. The main question raised in the model is to follow as much as possible the real conditions, since many models assume that the charging is up to full charge and the discharge is until the battery gets completed discharged. Then the battery capacity measurement each cycle is not necessarily the best approach. In summary, the method was about estimating the voltage drop in the diffusion branch, so the voltage drop associated with this can be estimated and then the state of health is known (comparing the initial voltage drop with the current voltage drop). Besides that, the direct measurement of the battery voltage and current are used to get more information of the state of health. In other words, while driving the electric car the voltage drop by diffusion cannot be directly measured, then the genetic algorithm is used to estimate the voltage in the diffusion branch. As the terminal voltage and the battery current can be measured, the voltage relationship is estimated cycle by cycle so the voltage drop in the capacitance changes and its compared with the rated capacitance. The state of health also accounts the voltage and current measurements; for example, the total voltage is also changing as the battery capacity diminishes. For estimating the capacitance value with the genetic algorithm, the prediction error minimization method is also used.

The battery was run for 253 cycles, at different conditions. The guideline for these conditions was the Urban Dynamometer Driving Cycle, so the first 109 cycles the charge and discharge was C/2 and C respectively (16 and 32 A). The next 98 cycles the charge and discharge was at 2C. And the following 43 cycles there was 1C for charge and 2C for discharge. Along 3 cycles the current for both processes was 1C. Each one of the charging processes lasted for 12 minutes and there was a minute rest before the discharging.

The resting time between cycles was 3 hours; therefore the voltage drop in the diffusion branch can be set to zero. With the model-estimated capacitance value, it was possible to calculate the voltage at each cycle. After 46 generations in the genetic algorithm the variation between the measured battery voltage and the model prediction was less than 0.005 V. So it can work if the vehicle is operating (the diffusion resistance along all the process is barely changing). With 95% accuracy level, it was proved that the battery capacitance change (that can be calculated with the model) is related with battery capacity. This relationship between the diffusion capacitance and the battery capacity is used to estimate the SOH in equation (5):

$$h = \left(\frac{b_1 C_{diff\_rat}}{C_{diff}} + b_0 \right) \times 100\% \qquad (5)$$

Experimental trials for temperature influence were conducted in a climatic chamber, BT 2000 battery test. The range was between 0 and 40 degrees. The relevant outcome was that as the temperature arises, the resistance decreases, whereas this did not happen with the number of cycles. Results are consistent since the higher the temperature, the higher the capacitance (the accuracy level for this was 95.35%).

Accounting the temperature influence the equation is (6):

$$h = \left(\frac{\left(a_1 T^2 + a_2 T + a_3\right) C_{diff\_rat}}{1000 \times C_{diff}} + b_0 \right) \times 100\% \qquad (6)$$

From the equation and experiment data, it can be inferred that the model can be applied to all Li-ion batteries as long as the pouch structure and the voltage levels are the same.

Battery model 3

Finally, the third battery model was developed by Zhang, Wang and Tang (2014) [9]. In spite of the fact that the experiment was used for a PHEV hybrid instead of an EV, the results are useful since the authors developed an indicator of how many miles the car can run in electric mode only, and testing how this indicator evolves as the car is used. The criteria for the minimum SOH of the battery in this case is that the minimum miles in electric only mode is 20. The used battery for the experiment was a $LiFePO_4$ prismatic (that means the cathode was carbon coated to improve the performance and the lifetime) with a capacity of 16.4 Ah. The experiment conducted by the team consisted in running the battery and evaluating the capacity and the electric only miles capacity after 300 and 600 cycles at different temperatures. The idea was to verify the battery performance in the EV. However, as the electric only miles is related with the battery capacity, and moreover, the electric-only capacity is a really close indicator of the state of health (when compared with the rated range), the assumption is to use it as key data,

For the experiments the EPA Urban Dynamometer Driving Schedule was used. From this one, the electric range was obtained. The charge and discharge was at 3C for every cycle. As written above, the tests at different temperatures were conducted at the cycle 300 and 600. The equipment used was the Arbin BT 2000 chamber and the Tenney Environmental equipment. During the test at different temperatures the resting time was 4 hours at 45, 0

and -10°C and 1hour for the test at 25°C. In order to simulate as much as possible the real driving circumstances, the SOC range at each cycle was between 30 and 80%.

This work did not develop an equation in order to consider the degradation or the state of health as function of the number of cycles, or as a function of temperature. So the task was to develop a way of relate this two variables with the SOH.

As previously explained, the experiments shown in that work provide information regarding the electric only mile range at different temperatures. And it is also stated that the operative temperature of the battery are the highest and the lowest ones were the experiments were conducted. So therefore a simple linear interpolation can be done using the given data as limits for each temperature sub range. Another approach might be to develop an equation using those points, but that is not practical since the points are very few and a small deviation could cause that the estimations are out of logical values (i.e. if a polynomial equation is applied).

After that process, data are available for all the temperatures (from -10°C to 45°C) at 0, 300 and 600 cycles. Then another interpolation needs to be created, given the mileage range at different ageing. And once there are data for each degree at each cycle, the mileage range table is complete.

Now, the SOH is defined by the ratio of the current mileage range with the rated range at the given temperature. This calculation way is valid in the ideal case that the cycles take place at the same temperature. However, as the cycles occur at a changing temperature every cycle, the ratio calculation is not necessarily reflecting the SOH value. In order to solve this issue, instead of calculating the SOH at each cycle, a degradation value is estimated and at the end the SOH accounts the degradations in all the cycles.

From the described models, the first one is the most flexible since the charging current and temperature can be changed. The main limiting factor is that at very extreme temperatures, the accuracy level is not the same. But from the experiment data, the range of temperatures where the model is acceptable is brought. The second model is the most limiting one, since the charge and discharge currents are specific as well as the number of cycles.

The third model is the most ambiguous in the sense that provides less information since the behavior is found and studied just after 300 and 600 degrees, then the linear approach is a very simple approximation method. However, as this work is focused in a trial period of one year, the projections from the 300th cycle onwards can be assumed close enough of what

happens in the experiment,

Assuming an equal charge and discharge rate will be essentially wrong, due to the types of batteries are different. The first and the third one models, even though they share a similar chemical structure, are not the same.

An important assumption is that the temperature value is the same for every cycle. Then for 365 cycles there are 365 temperature values for each case. The real case is that, especially for an EV application, the temperature is not the same simply because the ambient temperature is not necessarily constant and also as the battery resistance changes the temperature is affected due to the Joule effect. A more detailed explanation about the relationship between the ambient and the battery temperature is given in the following part.

It was mentioned that for the EV, the remaining capacity after each cycle is closely related with the SOH value and with the mileage distance. According with data from the EPA, the energy needed per mile is between 0.84 and 0.87 Wh per mile.

The main conclusion from these models is that a mathematic approach was found for an EV battery. And these models, with proven accuracy can be used for simulations at different temperatures as long as the same chemistry and battery structure is considered. These three models will be used at the three locations and the performance will be compared.

The next table shows the battery model features, as well as the commercially available cars that have a battery with a structure as the models to be compared.

Model	**Battery chemistry**	**Commercial brand for those batteries**
1	$LiFePO_4$	Chevy Spark
2	NMC	Ford Focus Electric
3	C-$LiFePO_4$	VW Golf

Table 2. The different models used and their features. Source: Electric car range comparison [19].

5.2. Locations

First of all, the different locations need to be defined. And those locations need to have a different temperature profile so the exercise is relevant to be conducted. Another guideline is to refer a country where there is at least a certain amount of EVs already commercial

available, so there are data to be realistic about the main constraints that exist in that place. In this line, it can be assumed that charging is possible at any time of the year, even as easy as charging fuel.

In order to do this, the most recent reports regarding EVs were consulted and according with the information provided by the company ABB, the list of the countries with a higher share of EVs in the total vehicle market has in the top Norway and the Netherlands, and after some European countries with a significant less share: Sweden, Denmark and the UK. The US and China have also a high share in terms of total units.

It is also important to set the location at a specific region of the country, in order to have a temperature that is more accurate on where the car is and also to really fulfill the condition that the EV can be charged properly. A city is suitable for a location, then the information about the place was collected. Moreover, assumptions about the daily mileage are more close to the reality. For every location, relevant information is included. The three locations are: Oslo in Norway, New Jersey in the United States, and Barcelona in Spain. According with the 2016 and 2017 EV outlook reports from the International Energy Agency, these three countries are among the ones with a highest share of EV, and therefore, with the biggest infrastructure in order to recharge the batteries [2,3].

Before analyzing the particular settings at each place, it is convenient to relate the battery temperature and the ambient temperature, since the key data from the three locations is the mean ambient temperature value.

In the previous chapters it has been explained the temperature as an important parameter for the performance and battery lifetime, and also that the BMS has a key importance in regulating the temperature within the range where the best performance and safety are reached. Also, that the thermal control can be done by air, liquid and that in the second case can be using energy from the same battery or energy from the grid. Depending on the location, and the particular conditions of the experiments that were done to validate the models explained before, there are some assumptions considered for this work.

In first place, for all the models it is assumed that are conducted with a BMS whose thermal management system is done with a liquid working fluid. The referred study conducted by the NREL gave as a result that for a high temperature, if a metalized solar reflective film is installed, the temperature will be maximum 2°C below the ambient temperature. In case of a cold weather, the PCM method will control the temperature so the difference between ambient temperature and battery temperature becomes less significant. If thermal preconditioning is applied, in a day with low temperatures, then the temperature increases so

the battery performs better. Based on the NREL estimations, this improvement conducts to a 1.7% on the driving mileage range. However, if the battery needs to be heated up and the energy to do this is coming from the battery itself, then the range is reduced in 3.9% [11].

Internally, it is assumed that the temperature profile in all the cells is fulfilling the requirements of the NREL for an EV, being that the difference between the coldest and hottest cell is not higher than 3°C and the battery can be considered as a whole body with the same temperature [11].

Also, the temperature is kept constant along the cycles, each cycle has its own temperature. A typical driver to and from work will get maybe not the average temperature of the day, but this is a valid approximation as the time when the car is driven is not having the highest nor the lowest temperature.

Barcelona, Spain

In spite of the fact that the EV market has not grown as much as in other European markets, the number of units show a considerable increase. In 2016, 4746 new electric vehicles were into the road in Spain, 51.5% more than 2015 (is also important to consider that the number of hybrids grew in 31019 units, meaning 68% in this category) [20].

The government incentives for purchasing an EV are regulated by the MOVEA Plan (Plan de Impulso a la Movilidad con Vehículo de Energías Alternativas), depending of the Economy, Industry and Competitiveness Ministry. The new regulations state that the government subsidies are 5500 € for an EV (defining a range of 90 km) in addition to 1000 € for installing a charging point. These grants are possible to get only if the price of the car is less than 32000 EUR (before 2015 this limit was 40000 €, it was reduced to increase the share of the EVs over the hybrid models) [20]. And it is not possible to combine them with subsidies coming from the local authorities, only if they come from EU funds. And finally, these subsidies are given only for a specific number of units, since there is a budget. This year the limit is 16.6 million Euros. The user needs to apply and will get the funds if they are available. There is also a deadline for application, being October 15th for 2016. In case of applying for the charging point grant, there is also a possibility to use it for the purchase, meaning that 6500 € are discounted (evaluating this depend on if the user has a garage for installing the charging point).

There are also subsidies that apply for companies. Each company was able to get up to 200000 € each for year. From 2017 onwards, this limit has been eliminated, being good news for medium and big companies. There are also funds for the entities that are interested in installing a charging point (i.e. 15000 € for a fast charging point) [21].

Together with the subsidies for purchasing, the EVs are exempt from paying registration taxes (they do not emit CO_2), they can get reduction in circulation taxes (this depends on the cities council), being for Barcelona a 75%. EVs can also use the special lanes (Bus-VAO, used for public transportation).

Referring specifically to Barcelona city, the council established a procedure to regulate the EVs. All the EV owners can apply for the EV Card, which identifies the car as an EV and allows using the public charging points for free. In addition to this, the card gives free parking in the regulated areas (in Barcelona are the green and blue places) [22]. Parking in local residential areas is not allowed) within specific times.

New Jersey, United States

The US play an important role for the EV industry. Even the market share of EVs in the total vehicles is not that high as in other countries (only 0.7% in 2015), as is one of the biggest markets, in terms of units was the biggest one until 2015, when China took the lead. In China the share was 1% by 2015. On that year, the new units sold were less than 2014 by 6%. By 2016, there was an increase of 38%, with 159 000 new cars sold. The growth rate is a good sign, however other countries the growth was more than 75% [23].

From all the new EVs sold, more than 50% were purchased in California. There were only 3248 new purchases in New Jersey. From total purchases in the country, Tesla models were the most sold.

The incentives for purchasing a car in the US can be funded from the federal government or from the state. In federal terms, the BEV and the PHEV purchased after 2010 can get a tax credit up to 7500 USD (however, once the manufacturer gets 200 000 sold units then this amount is reduced on 50%). Also, for charging stations, the tax credit is 30% or 1000 USD (the lowest) if its personal property, and when the station is for a company the tax credit is for 30000 USD or 30% (the lowest) [24, 25].

For the state of New Jersey, the REEV, FCEV, BEV are classified as zero emissions and are exempted for the state tax for selling and using. The zero emissions can use the carpool line. Also, if the fuel economy is equal or more than 45 miles per gallon the state offers a discount of 10% in the off peak New Jersey Turnpike. The discount is also available for the Garden State Parkway [26, 27].

Oslo, Norway

Norway is well known as the country that has a biggest share in EVs around the world, 23%

in 2015. In terms of total units, that means more than 18 157 vehicles in November of 2013. The target is to have 200 000 units in 2020 across Norway [28]. Hybrid models (PHEV) also have a strong presence; however they are out of the scope of this work.

The increase in the last years has been possible due to the policies that encourage people to choose EVs, like free parking, access to public transport lanes, free use of toll roads and ferries owned by the state (for ferries, the car goes for free and only the driver pays). There are also reductions in road taxes, being the fee 400 NOK for EVs and for combustion engines 2840 NOK. Also, charging is free at public charging points and new vehicle registration is not applicable. The most important incentive is that car sales taxes (VAT) are reduced 50% (on average, for vehicles the VAT for selling is 50%). The access to collective lanes for drivers is also a key factor in the Oslo area [29].

Moreover, the car owner in Norway has an environmental awareness about the impact of having a gasoline car and having an EV. Besides the free parking, many workplaces have the facility to charge the car at no cost. Not only private drivers have an EV, also companies do. Companies own 29% of the total EVs in Norway [30].

Oslo has temperatures each year in the range of -14 up 2°C in the winter season. As explained in the previous chapters, being in a cold weather such as Oslo one, implies many constraints that have to be addressed. A high resistance value and a high use of energy for heating up the battery several days per year are examples of this.

As a rule of thumb, the driving range in a cold temperature in Oslo (considering a cold day between -10 to -12 °C) will decrease 40 or 50% compared with the range at the optimal temperature. According with the research conducted by Johanssen, a change from 10 C to -10 C will drop the range by 50%. Estimation was conducted with the Nissan Leaf model (whose chemistry is LiMn) at two different temperatures in Oslo. At 24 C, the range was 137 km if travelling at 59 km/h. At -20 °C, the range was only 63 km (mainly due to the loss caused by heating up the battery) at 60 km/h. This estimation was done using the Gronn bil range calculator, a tool to estimate the range according with temperature, average speed and the road characteristics. It is also important to consider the charging at low temperatures, not only the discharging process while driving. If the charging is done at the public sites, then considering the ambient temperature is appropriate, since the car has been driven for a long distance (that is why it is discharged) and the battery is after driving, at a temperature highly influenced by the ambient temperature. Other situation might be also that the car is stopped for a while and then the temperature is the environment temperature so heating is needed. The charging energy value is higher and therefore the energy taken from the grid increases. A research made by VTT (Technical Research Centre of Finland) gave as a result that a

Citroen C-Zero EV model needs 0.23 kWh to run for 1 km at -20 C, in comparison with 0.174 kWh if the temperature is 23 °C. The gap is normally lower in urban areas than in the road.

A car driver in Norway everyday goes on average 38.5 km, and the number of trips is 3.3, considering that the average trip has a speed of 29.5 km/h. However, as the driving distance differs depending on the specific location, the mileage per day is 30.2 km is Oslo, according with the research made by Vagane (2011). In the cities those are located close to Oslo, the range increases considerably, being up to 48 km per day. And the results differ a lot with the car used for services, such the ones provided by the council: 42% of the cars of this group have a daily driving range between 50 and 100 km.

Another relevant data from Norway and particularly for Oslo are that the longest travels are for going to the workplaces, and the shortest for leisure. Also, on average the distance driven everyday is the same along the year (no significant differences between season, contrary on what happens in Sweden, where a longer distance is driven in the summer). 95 % of the private owners and 80% of the companies state that the distance is roughly the same. In addition to that, 74% of the drivers use the EV six or seven days per week.

Regarding the charging, in 2013 almost 10% of the charging points were fast charging, with this percentage on a trend to increase in the future [30]. The summary of the subsidies is listed in the next table.

	Purchasing	**Driving**
Barcelona	5500 € 1000 (charging point)	75% discount on circulation taxes No registration taxes Free charging and parking at specific times and areas
New Jersey	6818.18 € 909.09 (charging point)	No circulation taxes Carpool lane, discount in the NJ Tumpike
Oslo	50% of sale tax (roughly 25% of sale price)	2440 NOK reduction in road tax Use public transport lane and ferries Free parking at public places

		Free charging

Table 3. Subsidies summary for EVs at the different locations.

A benchmark in the economic side is also presented in this work, within the next chapters.

Final considerations

Another consideration is related with the dates of the trips done along the year. The models were conducted under the assumption that the cycle 1 is in January 1st, the cycle 2 in January 2nd and so on. In order to address this, the next tables provide information about the batteries to be compared and the mileage driving range in the three chosen locations.

Model	**Battery type**	**Driving range (km)**	**Driving daily needs (km)**	**Maximum time without recharging**
1	$LiFePO_4$ Chevy Spark	131.938	Barcelona 27.2	4.85 days
			New Jersey 35.336	3.73 days
			Oslo 30.2	4.36 days
2	NMC Ford Focus Electric	122.284	Barcelona 27.2	4.5 days
			New Jersey 35.336	3.46 days
			Oslo 30.2	4.05 days
3	C-$LiFePO_4$ VW Golf	133.547	Barcelona 27.2	4.9 days

			New Jersey 35.336	3.77 days
			Oslo 30.2	4.42 days

Table 4. Comparison of range and mileage driven at the chosen locations. Source: RekkEVide [28].

The table gives an idea about the recharging needs. However, many factors are important to consider, and technically it is wrong to divide the 366 days in the 2016 year by the days that the battery theoretically runs. There are many reasons for this. The main one is that, as explained in the Li-ion batteries chapter, a high value of DoD means a higher degradation. So to extend the lifetime the battery does not get completely discharged: the lower the DoD, the more cycles the battery will work. Also, the battery is not necessarily fully charged at each cycle (especially at high rate charging as explained). The temperature is of course an important variable in the initial range, as developed in the models. Moreover, the capacity will be reduced, so is not correct to consider a constant mileage range along the year. Finally, for a typical driver, the charging process needs to be before the battery runs out, and the driver will go to a charging point if the battery gets a low level.

For all these reasons, the criteria was to set each cycle for one day, meaning a charging process at a charging point and then the discharging by driving. To measure the accuracy of applying this assumption, the driving pattern is applied in another evaluation and the result presented later on.

Related with this (1 cycle per day of the year), the last assumption was not to account the effects of self-discharging, since the battery will be run every day of the year. After the results, some issues related with the driving habits at the chosen locations will be explained.

From the previous information about batteries that has been given in this work, it can be inferred that the reduction in the SOH will not be at the same rate, and it could also be, that, mathematically, at some cycles the value is increased. However, the trend will be inevitably to reduce the SOH value.

6. Results

After the models were set in the Matlab platform (the code is attached at the end of this document) with the correspondent temperatures, the results were organized in two categories: the results by battery model and the results by place.

First of all, the temperatures in the three places are presented. The values are given as January 1st is the day 1 and December 31st is the day 366. The temperature values correspond to 2016. As mentioned in the previous chapter, data were obtained from the official city websites [31,32,33].

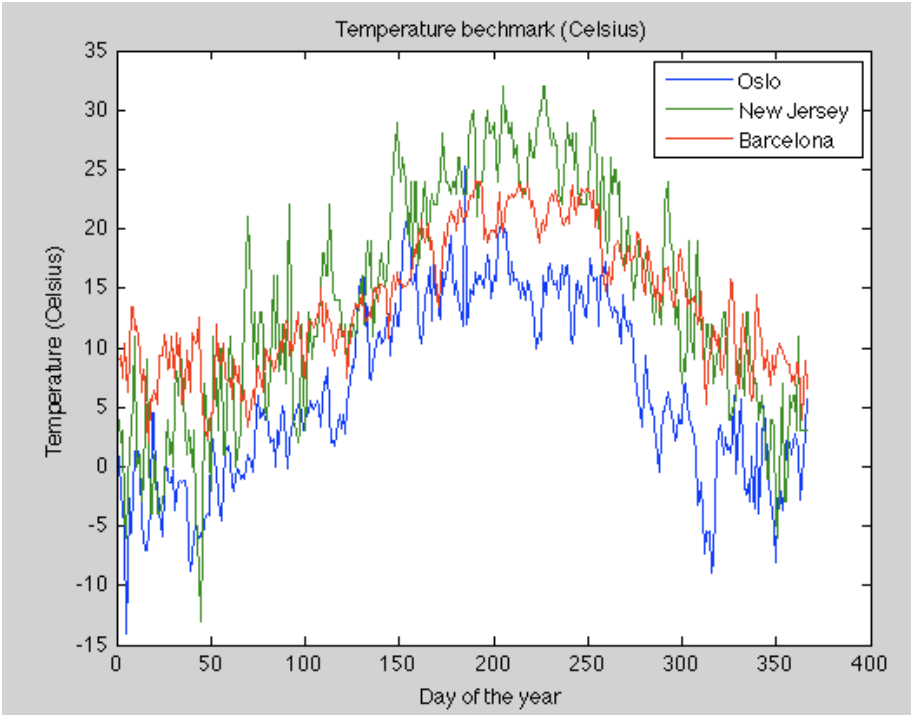


Figure 9. Temperature profiles along the year in the three locations.

The graph gives information not only about the temperature range but also about the variation of the temperatures each day, meaning that if the temperature changes drastically from one day to another, then the value of the SOH will also differ in a higher rate. It is found also that the more desirable environment is where the temperature is close to the optimal operation performance range. Also, that along the year the temperature range should not change a lot if the desired output is an extended battery lifetime.

For each result, there are two important values to take into account: the final SOH and the

trend that the SOH line was following. The smoother is the SOH line refers to more stability in the battery.

6.1. Results by model

The comparison by model aims to show more closely the influence of the temperature in the battery performance, as this is the only variable that changed in the exercise. It can be expected that the lower the temperature changes, the SOH values will also have small changes.

Type 1

The results show clearly that the temperature is a key variable as the older the battery becomes. In the first 100 cycles, temperature is not playing an important role, as the SOH values is almost the same. It is also important to consider that from the day 150 onwards summer arrives and the temperatures are higher in all locations, and after the cycle 300 temperatures go down again. This battery performs better in cold climates, therefore in Oslo will have a higher SOH at the end of the trial period. After 366 cycles reaches a value above 90%.

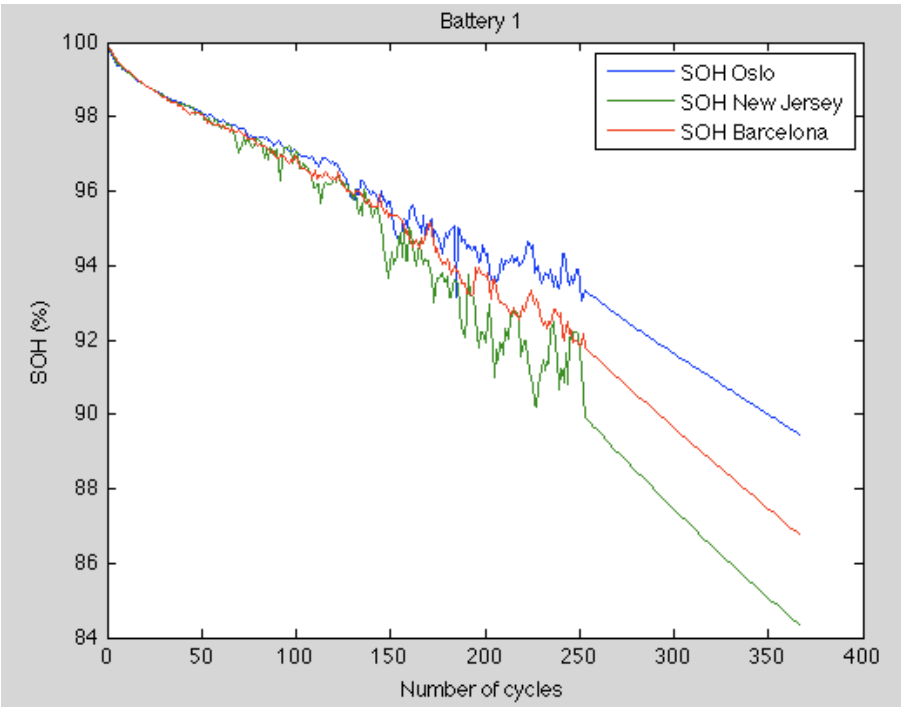


Figure 10. Results of the SOH for the $LiFePO_4$ battery

The results for this battery show that for Barcelona the SOH was 86.78%, for New Jersey was 84.34% and for Oslo was 89.46%. Therefore, this battery model is performing better at cold weather regions. And this becomes more evident as the older the battery gets, after the cycle 150, the battery in Oslo shows the best performance.

Type 2

For the three locations, the SOH value after the trial period is around 86%. The values along the year in the three locations are very close; however in Oslo the variations are higher. Also, in the season with higher temperatures the variations are reduced, so the model is more accurate as the ambient temperature values are higher. The main conclusion here is that the model is sensible to temperature but in average the mean result is not, as this sensibility represents variations in higher and lower estimations.

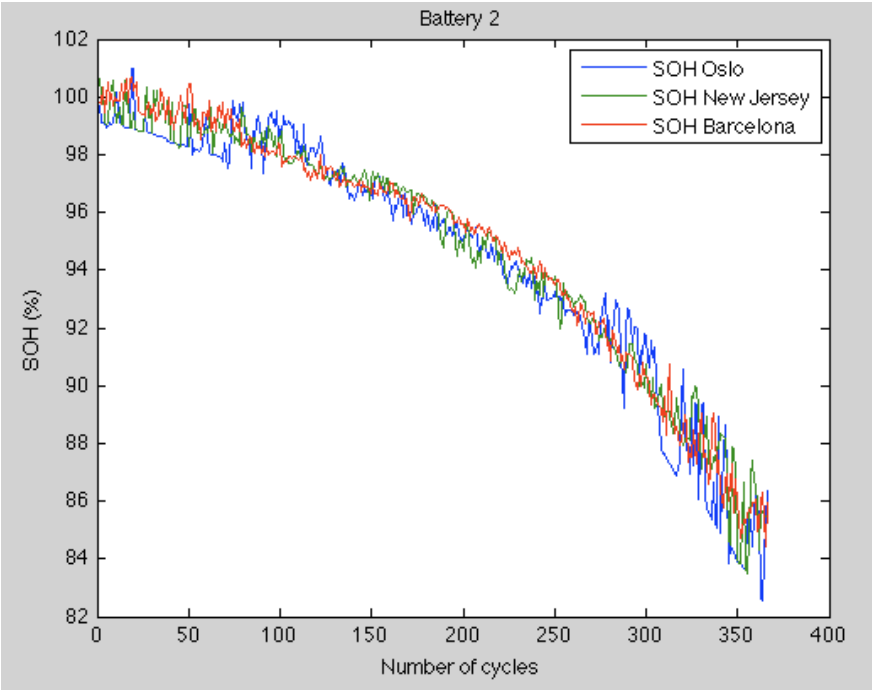


Figure 11. Results of the SOH for the NMC battery

The location in this case has not a very strong influence. In Barcelona, the SOH after 366 cycles is 85.97%, for New Jersey is 85.39% and for Oslo is 86.36%. Moreover, it is very difficult to name a city where the performance is better since at the latest cycles the value for the three locations is changing in each cycle in an oscillation way. In all the year, there is no clear result on which location is the most suitable.

Type 3

The results for this model show a nearly linear behavior because of the method followed to estimate the SOH. However, an advantage from this approach is to know directly what location is more suitable without analyzing the variations level. Along all cycles, the best location is Barcelona, then New Jersey and then Oslo. A clear conclusion is that the higher is the temperature level, the higher is the SOH. Also, as the number of cycles increases, this difference is bigger.

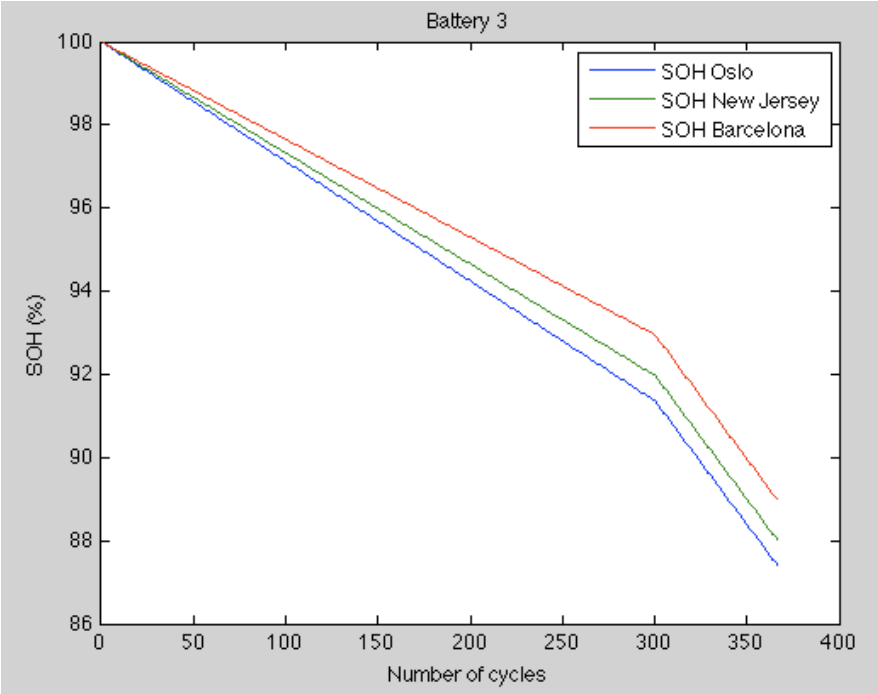


Figure 12. Results of the SOH for the C- LiFePO4 battery

For this type of battery the results are: in Barcelona, the final SOH is 89%, in New Jersey is 88.03% and in Oslo is 87.43%. Even though numerically may not represent a huge difference, after looking at the graph the result is that the performance in Barcelona is the optimal and for every cycle the SOH value is higher. Considering a year of operation, the

6.2. Results by place

Barcelona, Spain

The results for Barcelona show a little but significant difference referring to compare the different battery models.

The model 1 has the poorest performance along most of the year, and the more cycles there are the difference with the type 3 increases. So for Barcelona, the worst battery is the type,

not for the final SOH value, but for the degradation rate it has along all the cycles. The NMC (type 2) has a similar behavior than in the other two cities, but the SOH values are not very different from the other models (with the other locations, SOH is higher in the first 200 cycles). For this case, the best battery option is the type 3, since it is at 93% of SOH after 300 cycles; and even the degradation increases later on, still gets a better performance compared with the type 2.

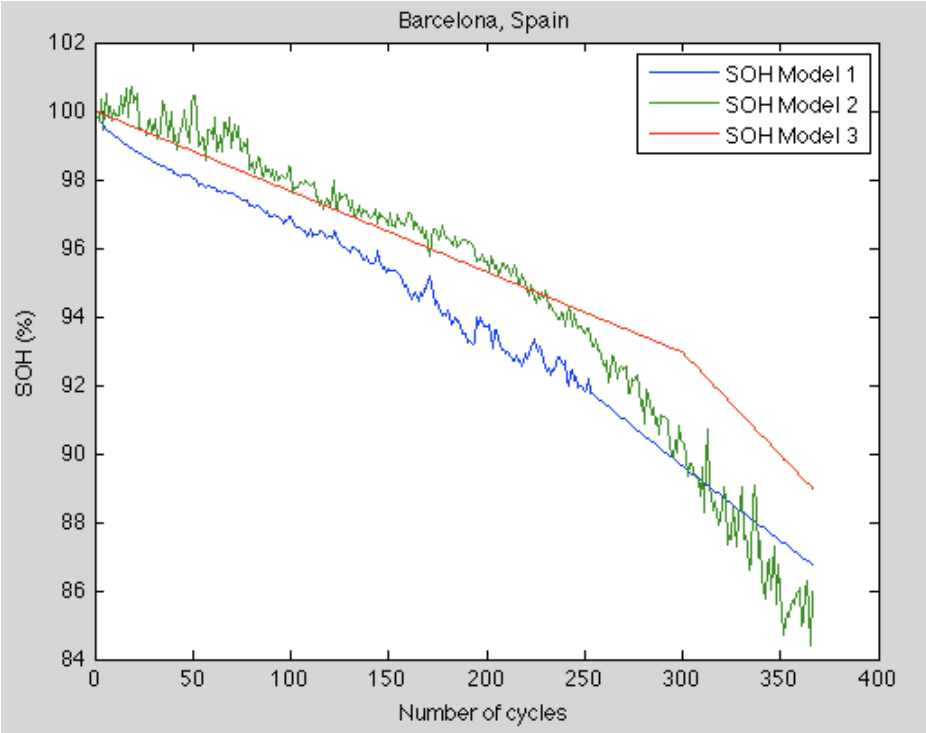


Figure 13. Results of the SOH for the different batteries in Barcelona.

One fact from the Barcelona comparison is that even the lines show a variation in the SOH values, these are not as high compared with the New Jersey. In NJ, the lowest temperature reaches very low levels; comparable with Oslo, but the hottest dy in the year shows a higher temperature than in Barcelona, being a more extreme weather location. The SOH values at the end of the year are: 86.78% for the model 1, 85.97% for the model 2, and 89% for the model 3.

New Jersey, US

As in the previous case, the results were similar about the final SOH value. In this case, the final SOH values are found between 86 and 89%. However, a very different behavior is seen along the year in comparison with Oslo results. The three batteries show small variations, even after 300 cycles, therefore the models are more accurate when the BMS is designed.

Model 1 and 3 show a very close result trend line as they are made with the same chemistry, and again, the model 2 shows a better performance at the beginning but after 250 cycles, the degradation rate is higher and becomes the battery with the lowest final SOH value.

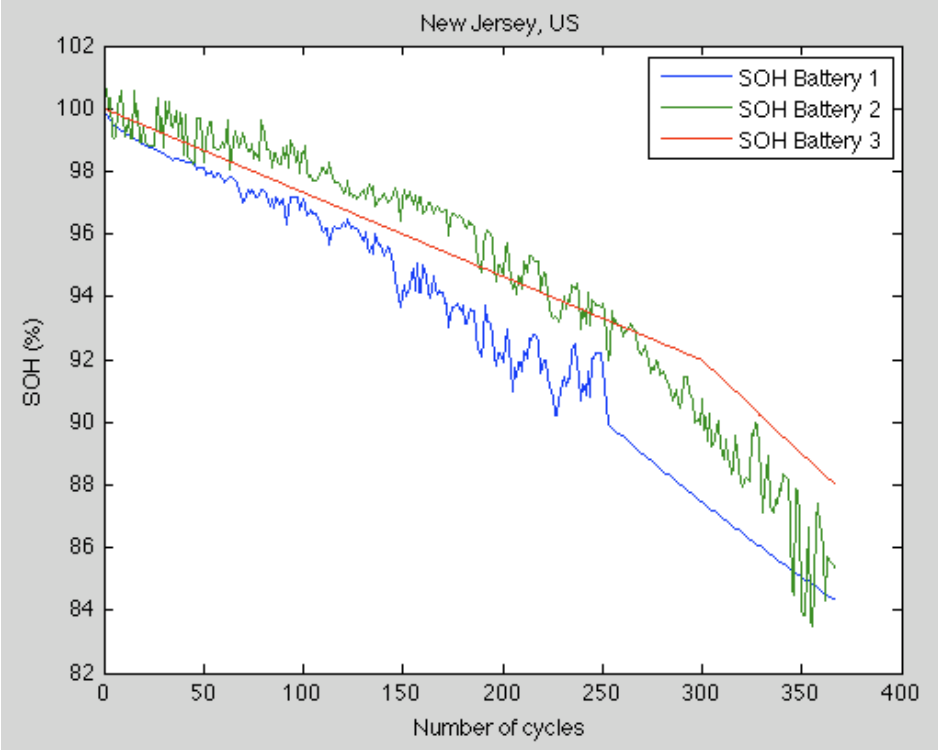


Figure 14. Results of the SOH for the different batteries in New Jersey

In New Jersey, the best performance is reached by the third battery, even though it shows a poorer performance in the second half of the year. Quantitatively, the results are: for the LiFePO4 battery, the final SOH is 83.34%, the NMC value is 85.39% and for the C-$LiFePO_4$ the SOH is 88.03%.

Oslo, Norway

The three types of battery show similar results when referring to the final value of SOH. For all the models, the SOH is still above 80, so the battery can continue working. However, the NMC battery is showing that as the number of cycle is higher, the SOH is oscillating in a bigger range. Model 1 and 3, based in $LiFePO_4$, show that differential of degradation increases after the cycle 300. After 366 cycles, for all the batteries, the SOH will be between 86 and 88%, if for each one of the cycles the temperature is the mean daily temperature.

In Oslo, the most suitable battery is the first type, whose chemistry is $LiFePO_4$. On the other

side, the worst choice would be the third type, also based in $LiFePO_4$.

However, if the results are based on the SOH value along the year, the first type is the best one, since the SOH was kept into a higher value compared with the other two. The third type shows more stability (given mostly by the mathematical approach followed to obtain the SOH), but with a SOH that is the lowest in most of the time evaluated.

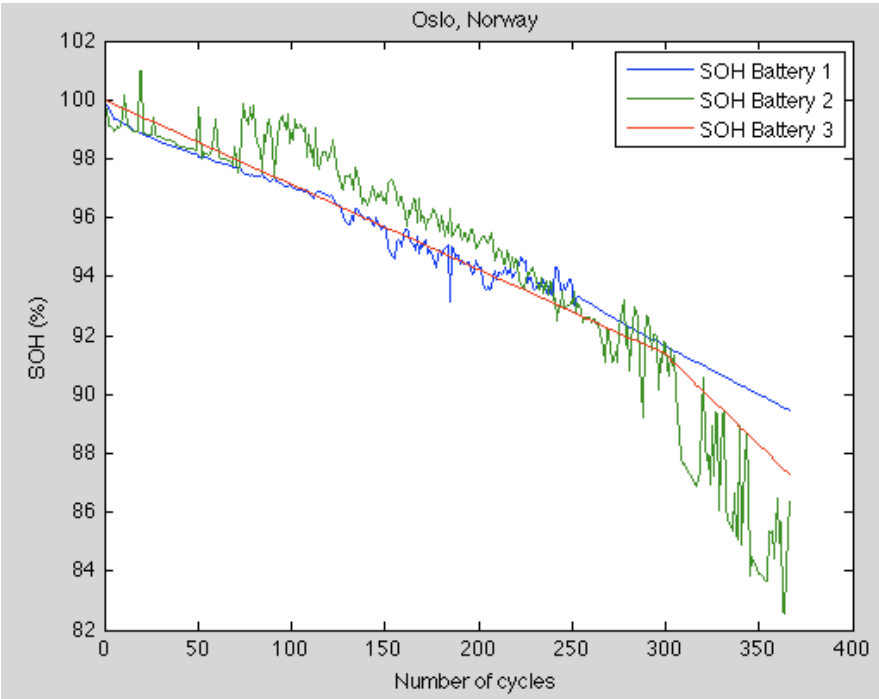


Figure 15. Results of the SOH for the different batteries in Norway

The results for Norway are presented again: battery 1 shows a final SOH of 89.46%, battery 2 has a 86.36% and the battery 3 keeps a SOH value of 87.3%. Therefore, in Oslo the best battery is the $LiFePO_4$ because it keeps a highest SOH value but moreover this value has a much lower variation in low temperatures (it changes more in the summer). This battery performs better in a cold weather.

The next table summarizes the results for the SOH values obtained in the model:

	Model 1 **$LiFePO_4$**	**Model 2** **NMC**	**Model 3** **C-$LiFePO_4$**
Barcelona	86.78%	85.97%	89.00%
New Jersey	83.34%	85.39%	88.03%

Oslo	89.46%	86.36%	87.30%

Table 5. SOH values for the different batteries at the chosen locations after 1 year of operation.

6.3. Driving mileage conditions

The previous results show the battery performance under the assumption that each cycle corresponds to one day. The number of the cycle is equal to the number of day of the year and the temperature is the same in all that cycle.

The battery, when charged, can last for certain number of miles before it needs to be recharged. So if the total distance per day is lower, the battery does not need to charge immediately after the car is stopped at the end of the day. On the other side, should the distance be higher, then the battery needs to be recharged before the end of the day.

A good approach to account for this factor is the driving pattern at each one of the cities. Depending of the region, there is information available in literature about the driving range. A comparative table is presented below for accounting the degradation with the driving patterns for one year of operation.

	Model 1 **Chevy Spark** (Original range 131.938 km)	**Model 2** **Ford Focus Electric** (Original range 122.284 km)	**Model 3** **VW Golf** (Original range 133.547 km)
Barcelona (9955.20 Km driven)	New range 114.496 km	New range 105.128 km	New range 118.857 km
New Jersey (12943.96 km driven)	New range 109.957 km	New range 104.418 km	New range 117.561 km
Oslo (11053.20 km driven)	New range 118.032 km	New range 105.604 km	New range 116.587 km

Table 6. Driving range after 366 cycles for each car model.

As it can be inferred, the results are not showing accuracy due to the driven distance is not the same. If this fact is accounted, then the degradation and the SOH change their value. The number of cycles, if charging from the lowest to the highest charge level (charging only when the battery gets empty), has been rounded.

	Model 1 **Chevy Spark** (Original range 131.938 km)	**Model 2** **Ford Focus Electric** (Original range 122.284 km)	**Model 3** **VW Golf** (Original range 133.547 km)
Barcelona (9955.20 Km driven)	Number of cycles: 75 SOH value: 97.39%	Number of cycles: 81 SOH value: 98.49%	Number of cycles: 74 SOH value: 98.26%
New Jersey (12943.96 km driven)	Number of cycles: 98 SOH value: 96.81%	Number of cycles: 105 SOH value: 97.93%	Number of cycles: 96 SOH value: 97.75%
Oslo (11053.20 km driven)	Number of cycles: 83 SOH value: 97.23%	Number of cycles: 90 SOH value: 98.06%	Number of cycles: 82 SOH value: 98.07%

Table 7. Number of cycles and SOH values after driving distances are considered. Data of annual driven distance: [22,23,28].

And finally, the table showing the real ranges is showed below.

	Model 1 **Chevy Spark** (Original range 131.938 km)	**Model 2** **Ford Focus Electric** (Original range 122.284 km)	**Model 3** **VW Golf** (Original range 133.547 km)
Barcelona (9955.20 Km driven)	New range 128.49 km	New range 120.44 km	New range 131.22 km

New Jersey (12943.96 km driven)	New range 127.73 km	New range 119.75 km	New range 130.54 km
Oslo (11053.20 km driven)	New range 128.28 km	New range 119.91 km	New range 130.97 km

Table 8. Driving range after one year for each car model.

6.4. Cost comparison analysis

It was mentioned in the first part of this work that the main drawback for the EV market share increasing is the cost of the battery, the lack of enough public policies in several countries and the needed infrastructure for the charging points.

As the aim of this work is to provide a comparison for the different models, each model will be compared for each place. The most important assumption to do is that the degradation implies a market value loss.

	Model 1 **Chevy Spark**	**Model 2** **Ford Focus Electric**	**Model 3** **VW Golf**
Barcelona	41245 €	39000 €	28050 €
New Jersey	41245 €	32995 €	31895 €
Oslo	41223 €	43700 €	32022 €

Table 9. Car models cost at each one of the chosen locations [23,34,35].

If the degradation is proportional to the lost car value, then for driving the car for one year, these will be the remaining values.

	Model 1 **Chevy Spark**	**Model 2** **Ford Focus Electric**	**Model 3** **VW Golf**
Barcelona	40168.50 €	38411.10 €	27561.93 €
New Jersey	39929.28 €	32312.00 €	31177.36 €

Oslo	40081.12 €	42852.22 €	31403.98 €

Table 10. Car models value after one year of driving.

If the rule of thumb of a minimum SOH of 80% is considered, then the lifetime of the vehicle is estimated. The next table gives the results.

	Model 1 **Chevy Spark**	**Model 2** **Ford Focus Electric**	**Model 3** **VW Golf**
Barcelona	7.66 years	13.24 years	11.49 years
New Jersey	6.27 years	9.66 years	8.88 years
Oslo	7.22 years	10.31 years	10.36 years

Table 11. Lifetime of each car model after considering driving distances.

Therefore, the cost for each model is detailed in the next table. It is assumed there is no request for the user to install a charging point

Model 1 **Chevy Spark**	**Car cost**	**Car cost after subsidies**	**Annual cost**	**Cost per driven km**
Barcelona	41245.00 €	35745.00 €	4666.44 €	0.47 €
New Jersey	41245.00 €	34426.81 €	5490.71 €	0.42 €
Oslo	41223.00 €	30917.25 €	4282.16 €	0.39 €

Table 12. Cost for an EV user at the three locations. Information of subsidies from the councils websites [20,23,29].

Oslo is the cheapest place to purchase an EV, mainly due to the big amount of subsidies given at reducing by 50% the sales tax. The big success of this policy has made the Norwegian representatives to discuss whether to keep this policy or reducing the subsidies after 2020.

7. Business proposal. EV League: What is the best car for me?

In the recent years, electrical vehicles (EV) have gained popularity due to the need to reduce environmental impact of the transportation sector, combined with energy independence seeking, and public policies that make EVs competitive with traditional cars powered with internal combustion engines only.

Together with the increase of electric vehicles in the market, new business models have been developed and implemented, most of them related with mobility and infrastructure, for example car sharing, optimal paths with available charging points, and parking. However, by the time a new person is considering buying a new EV and wants to know is advantages and disadvantages according with his lifestyle, it is hard to him to find an effective tool for making a decision.

This proposal refers to an app for potential car owners in order to choose the best electric vehicle according with the location, consumer driving needs and existing infrastructure for charging. The intention is not to be an app full of advertisements from the different car manufacturers, but to making EV features easily understood based on specific needs.

While a person is considering the option that his next car is an electrical, many questions arise to him. Some of them are: How spread are the charging points? Which car models are available in my country? Are there any tax incentives for EVs? In the long term, is it worthy to purchase an EV? Many other questions are in the driving range of the car, safety and lifetime compared with a traditional Internal Combustion Engine (ICE).

7.1. Problem

The last years statistics from the International Energy Agency (IEA) showing an increasing in the EVs are promising and represent positive news in the way of having a sustainable transportation sector: at the end of 2016 there were more than 2 million EV worldwide, from the 1.3 million that were there in 2015 [2,3].

The consumer demand needs to be high enough in order to reach many countries goals. About electric vehicles performance there is still a lack of information that is relevant. For the author of this document, a car driver who is thinking on purchasing a new model may consider an electrical vehicle because of some of the next reasons:

1. Environmental awareness. Even though people may not know the number of tons of CO2 that are reduced, they have an idea about the environmental impact of having an ICE compared with an EV. In Norway, environment is the second reason to decide getting an EV.

2. Subsidies and tax reduction. Subsidies and policies are the main reason why people purchase and EV. With these benefits, EVs are cost competitive, and by allowing the circulation in public transport lanes, a great advantage is given. Following the norwegian example, there is a clear idea about what are exactly the benefits of having an EV in term of subsidies and special circulation permits.

3. Operational costs (fuel prices). In the cities where subsidies are given, charging infrastructure is available and charging is for free in public areas. Therefore, the savings per year are equal to the annual expenditure in fuel. The drawback is the time needed for charging, and that is an incentive for increase the share of fast charging points.

4. Sucessful experience from an EV owner. As more users choose an EV, the benefits and satisfaction rate can be spread more quickly. And also there is room for innovation about sharing the experience. So far, the only tools available are web forums and some websites.

People who are thinking in purchasing a new car are hesitating in getting an EV due to the lack of punctual and quantitative data referred to the specific needs they have. In first place, knowing what are the available models at the location and the mileage range they offer. This is the very first step, but not the only one.

Information to customer cannot come only from car manufacturers since this is only providing advertisements to him without giving personalized data. There is no tool to collect punctual information about the driving habits and location. Data need to be collected from the customer in order to offer him a set of solutions that makes him decide more easily.

Moreover, for the current EV owners, the benefits and drawbacks are known but in some cases not estimated (how to answer the question if the investment was worth and by how much?).

7.2. Solution: EV League

The proposed solution can be summarized as follows: collecting and providing information about available EVs to the car drivers in order the customer chooses the right car model. If the owner gets his expectation fulfilled, this will contribute in the medium and long term to

increase the EVs market share in a much faster way. The simplest and best way to explain how the solution worksl is to describe the customer experience for a new car driver.

A person located in any European city is deciding what is the most suitable car for him. The user is considering to purchase an EV only if he finds more advantages than disadvantages. From the car manufacturer website he gets only very basic information. Then this person decides to download the application, EV League.

EV League will provide to the customer, based on his location, the needed information to make a decision. First, it will enlist the models available at the city, which charging points compatible with the models can be found in the area, what models were purchased by more people in the last year, as well as which ones are the best rated by other users. Then in a simple form the user will set his driving habits, being this the daily mileague (for example, pointing out in a map where his office is, or any other path he is taking frequently). Also, by typing the average time it takes to him to go to work, the average speed will be calculated. The final estimation will be the total distance he travels everyday.

Based on the temperature profile, considering the batteries that perform better in that temperature range is the next task. It will consider of course the battery types that are present in the available models. The program will have an algorithm that will calculate the effect in the capacity because of operating at those temperatures and by the ageing effect. In other words, based on the chemistry of the batteries, equations that account degradation by temperature and ageing will estimate the remaining capacity after each cycle. This algorithms will be contained in the program and will be built based on the different equations that correspond to degradation effect. Also the results will be compared with the technical information available from the car manufacturers whenever possible.

At the end, the customer will get a benchmark comparison between the available models. It will be stated which car is the cheapest, which one has the longest lifecycle, which one has more charging points, which model can be charged in less time, approximately how often he would need to recharge at one of the points, and which is the best rated by other users in the area. The customer can also read the reviews in each model if there is any.

The list and estimation of benefits (i.e tax reductions or free parking at any sites) will be displayed. Also, it will calculate how much money the driver would need to drive the total distance in the lifetime if he decides to buy an ICE (based on the current fuel prices). The aim is to get a database that can work as decribed at any European city.

The same or another user can use the performance evaluation tool in the app. Considering that the customer decided to get an EV, or another user has already an EV and wants to

track its performance, the evaluation tool will receive and provide information. The user needs to give as input whether the car is new or used (if this is the case, he will provide the mileage that the car already has) and the initial capacity will be esimated. Of course, he will provide the driving habits data, as in the previous case. The user can also give the charging time, just to check if the degradation is kept at a low level. News about incentives recently launched, new charging points and fees, and a comparison between the actual performance and the ideal performance is given (this is possible if the user provides data about the number of times he had to charge compared with the charging needs in a new EV model).

Having as basis the mileage, the driving habits and the charging time, and together with the algorithms, it will be possible to advice the owner when is convenient to take the car to the mechanical workshop to check out the battery status. Finally, the user will get information regading the replacement of the battery, how to dispose that battery, and all the regulations, procediments and registrations he needs to do according with his location.

The app will also have the traditional options: write reviews, check other user experiences, access to EV events at different locations and new versions available to be downloaded each time more accurate and detailed data are got and saved in the database. The app will be available to download for free. Users that want to follow up their car performance, as explained before, will be asked to purchase a Premium version.

The next table summarizes the hyphotesis proposed in this business model, and the way to validate these hyphotesis.

Hyphotesis	Validation
People hesitate in purchasing an EV due to lack of information	-Surveys -Studies made in different countries (such a RekkEVide)
A computarized tool based on mathematical models and local environment conditions can support an EV purchase decision	-Benchmark analysis -Model development -Experimental data from batteries and EVs on road
EV owners do not have specific information about the battery performance and status at every cycle.	-Research on information available at every city -Surveys with current EV users
An app for optimal EV model and EV performance tracking is attractive for people	-Surveys and beta version of the app for selected people -Number of users and number of Premium users -Reviews from the app itself, the website, social networks

Table 13. Hyphotesis to validate for the Business Model.

7.3. Business Model Canvas

Of course, the business opportunity will be to commercialize the app among the users. The app will be for free and will support the customer decision. However, performance evaluation and recommendations for an extended lifecycle and driving tips will be available only at a premium version. The business opportunity will be attractive also for car makers and for the different players along the EV chain. For example, car manufacturers concern not only about selling more, but also in knowing the perception the owners have about the charging points at any city. Lets say for example that there are only a few charging points that are compatible with that model. That is of course a signal to expand its infrastructure.

The sucess of this business will rely in first place in the accuracy of the models and the data management. For that, a lot of information needs to be collected. Without specific data on weather conditions, or city infrastructure information, or car models cost and features, its impossible to ensure a result and everything will be a guess.

Then the other part is the software development and marketing. An app needs to be presented in an innovative way, as the competition is hard (Apple Store, as an example, allows to download 140000 apps in a device). And most importantly about the business opportunity, the development has to be fast, since everyone can copy it. As mentioned before the comparison, there are aleady some range calculators in the Nordic countries available for EVs. Following the Canvas structure, here is presented the Business Model.

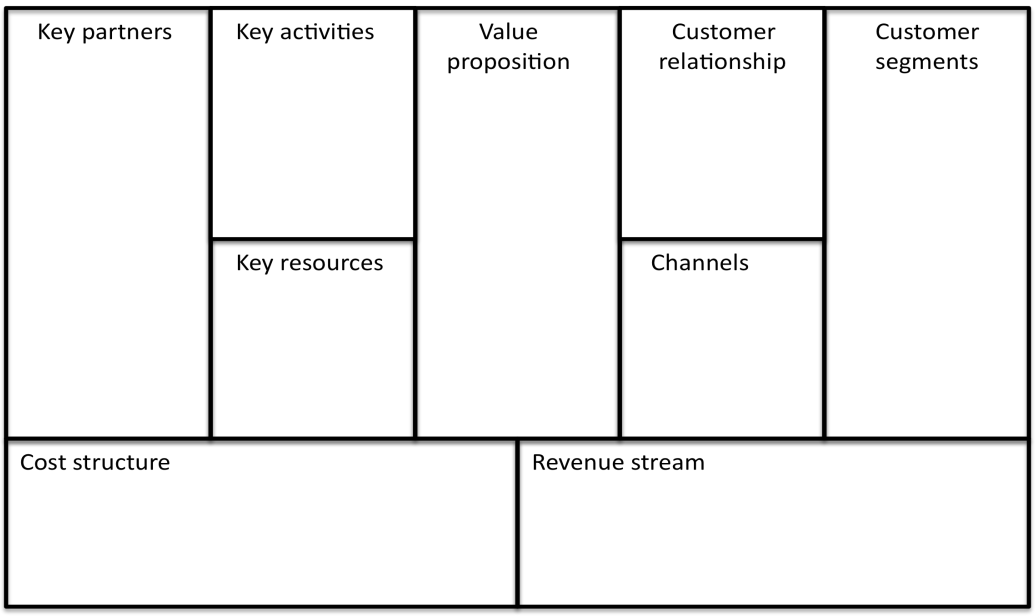


Figure 16. Business Model Canvas

Value Proposition

EV League will provide a complete evaluation for potential car owners in order to chooe the most suitable model. EV League will assist the EV owners in order to get the best possible economic, operational and environmental benefits.

Customer relationship

EV League will approach users by the digital tools available for apps. In the website the user will find all the information needed to understand how the app works and the convenience in getting the app.

The app users will be assisted when needed,

Among the users, there will be online support, a community manager and the received feedback will be checked in order to improve the customer service.

Channels

The most important channels will be the the plattform itself, the social networks (Facebook, Twitter, E-mail, website) and the events where the app will attend for promotion.

In order to be found for the potential or the actual EV owners, marketing strategy should be focused in the online material checked by people looking for cars.

Customer segment

Customers will be the people who are looking for a new car model and may consider an EV. But it not limited for the people who are making a decision. All the people interested in cars and that have along the last years checked other online tools can check the app and their feedback would be useful.

The users that purchase the app and ae doing a tacking on the vehicles are also considered as a different group.

Cost

Mainly the costs will be linked to the data management and updating and interface new features. As the data got are more specific and the number of cities where the app i developed grows, complexity will be added. Another initial costs will be related with the app design, and marketing.

Revenue

Revenue will come in first instance from the users that get the Premium version of the app, also the car manufacturers that are interested in some statistics from the performance of the models they sell can purchase some data.

It can be analyzed in a future analysis if including limited advertisement in the Basic version is convenient for the business plan (of couse, advertisement will disappear in the Premium version).

Key partners

The list of partners will be beggining from the weather forecast providers, the local autorities (who might be interested in some data from the performance and users prefeences), and car manufacturers (it is needed an access to the technical features of each model). Another important partner will be the universities on charge of developing new experiments and models that might fit in the app algorithms.

Private companies that develop software might be also important players, for example, if a patnerhip with a data security software is arranged. Also, in the long term, the exit strategy suggest to sold the app to one of these companies.

Key activities

EV League will be mainly focused in three activities related with data:

1. Data acquisition. Getting data from locations in first place, not only about the temperature values along the day everyday, but also about driving patterns, peak hours, pollution effects from engines, etc.

In a second phase, data acquisition refers to get from the app users the information concerning the preferred model in a city (both for simulation and eventually purchasing)

2.- Data management. This is related mainly with organizing the data in such way that models can be updated, results from users can be saved and organized in order to improve the models, getting statistics accoding to the place, and upgrading the capacity as the number of data will keep growing.

3.- Data presentation and design. As any other commercial software, an attractive design is needed. Functionality is also related to how only the relevant information, meaning with this only the information that is key for the user.

Key resources

The mot important resource is the information collected (by the research and the one from the users) meaning with that the software code. Also the human talent is a key resource, a the data management actions need to be conducted wisely.

7.4. Initial locations

The aim is to have a continous improvement in the app, therefore the algorithms will be improved and new versions will be available for the new users.

In order to increase the potential success for the app, the best location would be that one with high incentives and still low number of units on the road. In that situation, the app will be a very useful tool for people. The Netherlands and Spain show a great market for EV League. Locations such as Norway, and particularly Oslo, might sound a good idea at the beginning, but the awareness about the advantages for EVs are known by a high percentage of the population. Related with this, and as a criteria used also for the bechmark analysis presented in this document, the locations for the app should attach to cities and not by country (this is quite obvious, but really important).

Another criteria to choose the first location to launch the app could be the number of sold cars in the last years so the number of users is potentially higher. Also, more reviews would be available so a bigger community can be created there. In this case, of course China and the US will be top in the list.

The decision about which criteria should be prioritized is then the available information about local temperature, altitude, chaging points, and most importantly, driving patterns. The app will have a better performance only if the data about perfomance are enough for getting an accurate SOH estimation and performance analysis.

Moreover, even this idea may represent a novelty right now, there is absolutely no way to stop another entrepreneur or entity to develop it, so getting the highest recognition at the beginning is crucial for the business.

Having considered these factors, the best locations to start with are Amsterdam, Barcelona, Madrid and other norwegian cities such as Bergen.

7.5. Implementation steps

In order to stack up the business plan, the next one are the most important steps to follow.

1. Customer research needs. The best approach is to understand what are the customers needs regarding the cars purchasing.

A conducted research focused in Norway (RekkEVide) gave some insights that have to be addressed for the business strategy. The main motivator is to enlist the benefits that uing an EV has, then knowing in fist place if these benefits are well known by the people living there.

2. Data collection. This is the most important and difficult step. As personalized data based on the location will be provided, collecting the data for each place is a key priority. Temperature profiles for each city, charging point locations, and data from the driving patterns developed are just the beginning. Having this estimations of the ageing effect at different temperature and a different charge and discharge rate need to be estimated.

Besides the data from the place, data from the cars has to be collected. There are many models from the car manufacturers, and the technical especifications need to be checked to organize the data. The fields chosen are the ones related with performance and need to be filled. If for a car there is no enough information regarding the data needed, then simulations cannot be conducted nor presented. Innacurate results will cost credibility to the business.

3. Designing. It is not the intention of the app to give a ponderation to each indicator (cost, range, etc.) and to show what is the best option after using a black box. The aim of the app is to simulate the performance of the available cars and show the results to the user. People will take the decision based on those results and their personal preferences (color, brand, size).

So an attractive design is key for getting more users. Also, a user friendly design thinking that the people want concise data and indicators they cannot find somewhere else.

4. Marketing. As mentioned before, the app is a decision support tool and has to be marketed like it. In order to how the simulation results, options should be listed according with the users preferences. Marketing the product as an app will let people know that it is easy to use bacause normally they are using a lot.

Based on the marketing results with each design, the app will be adapted and modified to be more approachable.

7.6. Defined KPIs

The next Key Performance Indicators will be used to evaluate the business results:

1. Number of cities covered. The number of cities will define the potential number of users, then the complexity and size of the database.

2. Number of users. This one refers to the total users (downloads), the total Premium users (subcriptions), the rate of total users by the total EV owners registered, the ratio of users by the total car owners (EVs and ICE).

3. Number of car models evaluated. The more models available for simulation in the app, the more options can be given to the users. And also it requires more work to establish new algorithms as the battery characteristics change fom one brand to the other.

4. Application rate. About the feedback, users will be asked to provide it. Comments will be used to include/delete options, redesigning and designing the new versions.

7.7. Contribution in sustainable development

Providing the most suitable EV to the customer will increase his satisfaction and of course will contribute to increase the number of EV on the road. As the current policies, and particularly subsidies, are encouraging to place the EVs as an attactive option, people should have as much information as possible to choose based on their own needs [36,37,38].

Transportation is a major contributor to the GHG emissions around the world, and EVs can help in this task [42,43]. According with IEA, 23% of the greenhouse gases (GHG) are in transportation field [2,3].

Finally, as the intention is to provide a full sustainable solution, there is a huge opportunity area regarding the EVs. As briefly mentioned at the beginning of the document, the innovtion should come in all the lifecycle. Related with this, some batteries that are not useful for being put into a car and work as the power source may have another use. What about using batteries as part of stand alone energy projects in rural areas or developing countries?

8. Discussion

The temperature has not a big influence in the final values, but it has an influence on the specific SOH value each day. So even, the difference between models is not high if looking at the SOH after 366 cycles, the path to reach this is significantly different.

For the three places, the temperature values show that along the days the average temperature is not changing much in almost all the cases, and therefore the degradation is not as high from a day to the previous one. There are some exceptions for this, and those are the days where the degradation is higher.

The experiment conducted by Zhang and Quan gave as a result that the degradation from temperature from one cycle to the next one is way higher than the degradation from one cycle to another if these two are conducted at the very same temperature [39,40,41]. Conducted with $LiFePO_4$ chemistry, this experiment showed that the degradation for 200 cycles at the optimal temperature (20°C) was only 1.24 Ah, whereas the degradation from one cycle to another (at 20°C and -20°C respectively) was 19.5 Ah. The examples previously mentioned are related with this.

Conclusions

The EV industry is growing at a significant rate, mainly due to the policies that make electrical vehicles cot competitive and the benefits provided to the users. The growth rate will rely on keeping the policies aiming a long-term higher share.

The SOH and the SOC are two key indicators for the EV battery that have been deeply analyzed and modeled. Depending on the complexity level, and the approach taken, both values can be accurately estimated. However, there is still a lack in available models for SOH estimation with different temperature value at each cycle. It is important to work further in these models in order to consider the geographical conditions and their influence in battery performance.

The results presented in this document showed that the SOH differ from 1 to 3% only due to the temperature profile. However, the relevant results are got when the SOH value is analyzed along the year. It is not enough to point out the last value, but to see how this value has changed along the year. By doing this, two important findings are that the older the battery is, the uncertainty level increases.

If the driving distances at each one of the three locations are considered, then there is a lower difference in the SOH value. In spite of this, due to the range of the EVs and the daily distance, the lifetime of the car is really different from one place to the other, having even 3 years of difference, as resulting in the model 2. Therefore, on average, the SOH values are lower for the NMC battery, but after accounting the range and the frequency of charging, then this battery has an advantage. The NMC battery works better in hot temperatures, as the carbon coated $LiFePO_4$, whereas the normal $LiFePO_4$ works better in cold environments, if 366 cycles are considered (charging every day). If the charging happens only when the battery gets empty, after one year of operation the carbon coated shows better performance in cold weather and the normal $LiFePO_4$ in hot temperatures. For the long-term operation, the charging has to be done as many times as possible.

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9. Annex: Matlab code

```
%model 1
%LiFePO4

%Cr-degradation
%m and n are dependant in temperature
%N-numberofcycles


temp_oslo=zeros(365,1);
temp_oslo=importdata('Oslo_Kelvin.txt'); %temperature in Kelvin
temp_nj=zeros(365,1);
temp_nj=importdata('NewJersey2_Kelvin.txt'); %temperature in Kelvin
temp_bcn=zeros(365,1);
temp_bcn=importdata('Barcelona_Kelvin.txt'); %temperature in Kelvin

Ich=0.5; %charge current
Idisch=1; %discharge current


for j=1:366
    cycle(j)=j;

Cr2ch_oslo(j)=(0.01656)*(Ich^0.3428)*exp(942.67/temp_oslo(j))*(cycle(j)^(
14.235*(Ich^0.1595)*exp(-1059.63/temp_oslo(j))));

Cr2disch_oslo(j)=(0.01656)*(Idisch^0.1905)*exp(942.67/temp_oslo(j))*(cycl
e(j)^(14.235*(Idisch^0.0257)*exp(-1059.63/temp_oslo(j))));


Cr2ch_nj(j)=(0.01656)*(Ich^0.3428)*exp(942.67/temp_nj(j))*(cycle(j)^(14.2
35*(Ich^0.1595)*exp(-1059.63/temp_nj(j))));

Cr2disch_nj(j)=(0.01656)*(Idisch^0.1905)*exp(942.67/temp_nj(j))*(cycle(j)
^(14.235*(Idisch^0.0257)*exp(-1059.63/temp_nj(j))));


Cr2ch_bcn(j)=(0.01656)*(Ich^0.3428)*exp(942.67/temp_bcn(j))*(cycle(j)^(14
.235*(Ich^0.1595)*exp(-1059.63/temp_bcn(j))));

Cr2disch_bcn(j)=(0.01656)*(Idisch^0.1905)*exp(942.67/temp_bcn(j))*(cycle(
j)^(14.235*(Idisch^0.0257)*exp(-1059.63/temp_bcn(j))));


    if j<254
        Cr2_oslo(j)=Cr2ch_oslo(j)*Cr2disch_oslo(j);
        Cr2_nj(j)=Cr2ch_nj(j)*Cr2disch_nj(j);
        Cr2_bcn(j)=Cr2ch_bcn(j)*Cr2disch_bcn(j);
        SOH_oslo(j)=100-Cr2_oslo(j);
        SOH_nj(j)=100-Cr2_nj(j);
        SOH_bcn(j)=100-Cr2_bcn(j);
```

```
    else

growthfactor=[1.00305618,1.003044105,1.003032126,1.003020241,1.003008448,
1.002996747,1.002985137,1.002973617,1.002962185,1.00295084,1.002939582,1.
00292841,1.002917322,1.002906318,1.002895397,1.002884558,1.002873799,1.00
286312,1.002852521,1.002841999,1.002831555,1.002821187,1.002810895,1.0028
00678,1.002790535,1.002780465,1.002770467,1.002760542,1.002750686,1.00274
0902,1.002731186,1.002721539,1.00271196,1.002702448,1.002693003,1.0026836
23,1.002674309,1.002665059,1.002655873,1.00264675,1.002637689,1.00262869,
1.002619752,1.002610875,1.002602058,1.0025933,1.002584601,1.002575961,1.0
02567377,1.002558851,1.002550381,1.002541967,1.002533609,1.002525305,1.00
2517055,1.00250886,1.002500717,1.002492627,1.002484589,1.002476603,1.0024
68668,1.002460784,1.00245295,1.002445166,1.002437431,1.002429744,1.002422
106,1.002414516,1.002406974,1.002399478,1.002392029,1.002384626,1.0023772
68,1.002369956,1.002362689,1.002355466,1.002348287,1.002341152,1.00233406
,1.002327011,1.002320005,1.00231304,1.002306117,1.002299236,1.002292395,1
.002285595,1.002278835,1.002272115,1.002265435,1.002258793,1.002252191,1.
002245627,1.002239101,1.002232613,1.002226163,1.002219749,1.002213373,1.0
02207033,1.002200729,1.002194461,1.002188229,1.002182032,1.00217587,1.002
169743,1.00216365,1.002157591,1.002151567,1.002145575,1.002139617,1.00213
3692,1.0021278,1.00212194,1.002116112,1.002110317];

tempfactor2=[0.005800711,0.006025919,0.006251127,0.006476335,0.006701543,
0.006926751,0.007151959,0.007377167,0.007602375,0.007827583,0.008052791,0
.008277999,0.008503207,0.008728415,0.008953623,0.009178831,0.00940404,0.0
09629248,0.009854456,0.010079664,0.010304872,0.010856441,0.011408011,0.01
1959581,0.012511151,0.01306272,0.01361429,0.01416586,0.01471743,0.0152689
99,0.015820569,0.016372139,0.016923709,0.017475278,0.018026848,0.01857841
8,0.019129988,0.019681557,0.020233127,0.020784697,0.021336267,0.022799135
,0.024262004,0.025724872,0.027187741,0.026159917,0.027622785,0.029085654,
0.030548522,0.032011391,0.033474259,0.034937128,0.036399997,0.037862865,0
.039325734,0.040788602,0.042251471,0.04371434,0.045177208,0.046640077,0.0
50593638,0.183713747,0.316833856,0.449953965,0.583074074,0.716194183,0.84
9314293,0.982434402,1.115554511,1.24867462,1.381794729,1.514914838,1.6480
34947,1.781155056,1.914275165,2.047395274,2.180515383,2.313635492,2.44675
5601,2.57987571,2.71299582];

       Cr2_oslo(j)=(Cr2_oslo(j-1)+tempfactor2(round(temp_oslo(j))-
252))*growthfactor(j-253);
       Cr2_nj(j)=(Cr2_nj(j-1)+tempfactor2(round(temp_nj(j))-
252))*growthfactor(j-253);
       Cr2_bcn(j)=(Cr2_bcn(j-1)+tempfactor2(round(temp_bcn(j))-
252))*growthfactor(j-253);
       SOH_oslo(j)=100-Cr2_oslo(j);
       SOH_nj(j)=100-Cr2_nj(j);
       SOH_bcn(j)=100-Cr2_bcn(j);

    end

end
plot(cycle, SOH_oslo, cycle, SOH_nj, cycle, SOH_bcn)
title('Battery 1')
xlabel('Number of cycles')
ylabel('SOH (%)')
legend('SOH Oslo','SOH New Jersey','SOH Barcelona')
```

```
%model2


a1=0.0041;%constant
a2=-2.684;%constant
a3=-35.12;%constant
b0=1.105; %constant
%Cdiffrated=1632.36; %capacitance in faraday
b1=-0.03512; %value of b1 for alternative formula, special case of
freezing temperatures


%temperature in Celsius, it is from 0 to 40


temp_oslo=zeros(365,1);
temp_oslo=importdata('Oslo_Celsius.txt'); %temperature in Celsius
temp_nj=zeros(365,1);
temp_nj=importdata('NewJersey2_Celsius.txt'); %temperature in Celsius
temp_bcn=zeros(365,1);
temp_bcn=importdata('Barcelona_Celsius.txt'); %temperature in Celsius


for i=1:366
    N(i)=i;
    if temp_oslo(i)>0

tempfactor=[0.309043348,0.347809307,0.386618148,0.425426989,0.46423583,0.
50309368,0.516013624,0.528982577,0.54195153,0.554920483,0.567956823,0.596
192016,0.624433336,0.652674655,0.680915974,0.70916342,0.738145997,0.76722
6592,0.796307187,0.825387782,0.854584773,0.883610233,0.912690828,0.941771
423,0.970852018,1,1.003246833,1.006867358,1.010487883,1.014108407,1.01810
2624,1.04292558,1.067754662,1.092583744,1.117412826,1.142248034,1.1799112
94,1.217611311,1.255311328,1.293011346,1.330760371]
        Cdiffrated_oslo=1632.36;

        Cdiff_tempfactor_oslo=tempfactor(round(temp_oslo(i))+1);


        if i<14
            Cdiff_oslo(i)=(-(0.255*i)+1632)*Cdiff_tempfactor_oslo;
%capacitance, it will change each cycle

        else
                Cdiff_oslo(i)=(-(2.732*i)+1659)*Cdiff_tempfactor_oslo;
%capacitance, it will change each cycle
        end


h_oslo(i)=(((((a1*temp_oslo(i)^2)+(a2*temp_oslo(i))+a3)*Cdiffrated_oslo)/
(1000*Cdiff_oslo(i)))+b0)*100; %SOH in percentage

    else
```

```
tempfactor=[0.309043348,0.308718781,0.308394213,0.308069646,0.307745078,0
.307420511,0.307095944,0.306771376,0.306446809,0.306122241,0.305797674,0.
305473106,0.305148539,0.304823971,0.304499404,0.304174836,0.303850269,0.3
03525701];
        Cdiffrated_oslo=1632.36;

        Cdiff_tempfactor_oslo=tempfactor(abs(round(temp_oslo(i)))+1);

        if i<14
            Cdiff_oslo(i)=(-(0.255*i)+1632)*Cdiff_tempfactor_oslo;
%capacitance, it will change each cycle


        else
                Cdiff_oslo(i)=(-
(2.732*i)+1659)*Cdiff_tempfactor_oslo;%capacitance, it will change each
cycle
        end

    h_oslo(i)=(b1*(Cdiffrated_oslo/Cdiff_oslo(i))+b0)*100;
        end
end



for i=1:366
    N(i)=i;
    if temp_nj(i)>0

tempfactor=[0.309043348,0.347809307,0.386618148,0.425426989,0.46423583,0.
50309368,0.516013624,0.528982577,0.54195153,0.554920483,0.567956823,0.596
192016,0.624433336,0.652674655,0.680915974,0.70916342,0.738145997,0.76722
6592,0.796307187,0.825387782,0.854584773,0.883610233,0.912690828,0.941771
423,0.970852018,1,1.003246833,1.006867358,1.010487883,1.014108407,1.01810
2624,1.04292558,1.067754662,1.092583744,1.117412826,1.142248034,1.1799112
94,1.217611311,1.255311328,1.293011346,1.330760371]
        Cdiffrated_nj=1632.36;

        Cdiff_tempfactor_nj=tempfactor(round(temp_nj(i))+1);


        if i<14
            Cdiff_nj(i)=(-
(0.255*i)+1632)*Cdiff_tempfactor_nj;%capacitance, it will change each
cycle

        else

                Cdiff_nj(i)=(-(2.732*i)+1659)*Cdiff_tempfactor_nj;
%capacitance, it will change each cycle

        end
```

```
h_nj(i)=(((((a1*temp_nj(i)^2)+(a2*temp_nj(i))+a3)*Cdiffrated_nj)/(1000*Cd
iff_nj(i)))+b0)*100; %SOH in percentage

    else

tempfactor=[0.309043348,0.308718781,0.308394213,0.308069646,0.307745078,0
.307420511,0.307095944,0.306771376,0.306446809,0.306122241,0.305797674,0.
305473106,0.305148539,0.304823971,0.304499404,0.304174836,0.303850269,0.3
03525701];
        Cdiffrated_nj=1632.36;

        Cdiff_tempfactor_nj=tempfactor(abs(round(temp_nj(i)))+1);



        if i<14
            Cdiff_nj(i)=(-(0.255*i)+1632)*Cdiff_tempfactor_nj;
%capacitance, it will change each cycle


        else

                Cdiff_nj(i)=(-(2.732*i)+1659)*Cdiff_tempfactor_nj;

        end
    h_nj(i)=(b1*(Cdiffrated_nj/Cdiff_nj(i))+b0)*100;

    end
end




for i=1:366
    N(i)=i;
    if temp_bcn(i)>0

tempfactor=[0.309043348,0.347809307,0.386618148,0.425426989,0.46423583,0.
50309368,0.516013624,0.528982577,0.54195153,0.554920483,0.567956823,0.596
192016,0.624433336,0.652674655,0.680915974,0.70916342,0.738145997,0.76722
6592,0.796307187,0.825387782,0.854584773,0.883610233,0.912690828,0.941771
423,0.970852018,1,1.003246833,1.006867358,1.010487883,1.014108407,1.01810
2624,1.04292558,1.067754662,1.092583744,1.117412826,1.142248034,1.1799112
94,1.217611311,1.255311328,1.293011346,1.330760371]
        Cdiffrated_bcn=1632.36;

        Cdiff_tempfactor_bcn=tempfactor(round(temp_bcn(i))+1);


        if i<14
            Cdiff_bcn(i)=(-(0.255*i)+1632)*Cdiff_tempfactor_bcn;
%capacitance, it will change each cycle
```

```
        else

                Cdiff_bcn(i)=(-(2.732*i)+1659)*Cdiff_tempfactor_bcn;
%capacitance, it will change each cycle


        end

h_bcn(i)=(((((a1*temp_bcn(i)^2)+(a2*temp_bcn(i))+a3)*Cdiffrated_bcn)/(100
0*Cdiff_bcn(i)))+b0)*100; %SOH in percentage

    else

tempfactor=[0.309043348,0.308718781,0.308394213,0.308069646,0.307745078,0
.307420511,0.307095944,0.306771376,0.306446809,0.306122241,0.305797674,0.
305473106,0.305148539,0.304823971,0.304499404,0.304174836,0.303850269,0.3
03525701];
        Cdiffrated_bcn=1632.36;


        Cdiff_tempfactor_bcn=tempfactor(abs(round(temp_bcn(i)))+1);

        if i<14
            Cdiff_bcn(i)=(-(0.255*i)+1632)*Cdiff_tempfactor_bcn;
%capacitance, it will change each cycle


        else

                Cdiff_bcn(i)=(-(2.732*i)+1659)*Cdiff_tempfactor_bcn;

        end
    h_bcn(i)=(b1*(Cdiffrated_bcn/Cdiff_bcn(i))+b0)*100;
    end
end









plot(N, h_oslo, N, h_nj, N, h_bcn)
title('Battery 2')
xlabel('Number of cycles')
ylabel('SOH (%)')
legend('SOH Oslo','SOH New Jersey','SOH Barcelona')


%SOH deviation at different temperatures accounted
```

```
%model 3

%experimental data from EPA-US

%Initial potential-mileage

temp_oslo=zeros(366,1);
temp_oslo=importdata('Oslo_Celsius.txt'); %temperature in Celsius
temp_nj=zeros(366,1);
temp_nj=importdata('NewJersey2_Celsius.txt'); %temperature in Celsius
temp_bcn=zeros(366,1);
temp_bcn=importdata('Barcelona_Celsius.txt'); %temperature in Celsius


rated_mileage=[21,21.27,21.54,21.81,22.08,22.35,22.62,22.89,23.258,23.626
,23.994,24.362,24.73,25.098,25.466,25.834,26.202,26.57,26.7272,26.8844,27
.0416,27.1988,27.356,27.5132,27.6704,27.8276,27.9848,28.142,28.2992,28.45
64,28.6136,28.7708,28.928,29.0852,29.2424,29.3996,29.5568,29.714,29.8712,
30.0284,30.1856,30.3428,30.5,30.516,30.532,30.548,30.564,30.58,30.596,30.
612,30.628,30.644,30.66,30.676,30.692,30.708,30.724,30.74,30.756,30.772,3
0.788,30.804,30.82];
mileage_300=[18.33,18.56714286,18.80428571,19.04142857,19.27857143,19.515
71429,19.75285714,19.99,20.413,20.836,21.259,21.682,22.105,22.528,22.951,
23.374,23.797,24.22,24.4192,24.6184,24.8176,25.0168,25.216,25.4152,25.614
4,25.8136,26.0128,26.212,26.4112,26.6104,26.8096,27.0088,27.208,27.4072,2
7.6064,27.8056,28.0048,28.204,28.4032,28.6024,28.8016,29.0008,29.2,29.229
,29.258,29.287,29.316,29.345,29.374,29.403,29.432,29.461,29.49,29.519,29.
548,29.577,29.606,29.635,29.664,29.693,29.722,29.751,29.78];
mileage_600=[13.19,13.36,13.53,13.7,13.87,14.04,14.21,14.38,14.889,15.398
,15.907,16.416,16.925,17.434,17.943,18.452,18.961,19.47,19.638,19.806,19.
974,20.142,20.31,20.478,20.646,20.814,20.982,21.15,21.318,21.486,21.654,2
1.822,21.99,22.158,22.326,22.494,22.662,22.83,22.998,23.166,23.334,23.502
,23.67,23.8145,23.959,24.1035,24.248,24.3925,24.537,24.6815,24.826,24.970
5,25.115,25.2595,25.404,25.5485,25.693,25.8375,25.982,26.1265,26.271,26.4
155,26.56];
totalwear_oslo=0;
totalwear_nj=0;
totalwear_bcn=0;

for i=1:366
    N(i)=i;
    if i<=300
        cycle0_oslo=rated_mileage(round(temp_oslo(1))+18);
        cycle300_oslo=mileage_300(round(temp_oslo(1))+18);
        cycle600_oslo=mileage_600(round(temp_oslo(1))+18);

        cycle0_nj=rated_mileage(round(temp_nj(1))+18);
        cycle300_nj=mileage_300(round(temp_nj(1))+18);
        cycle600_nj=mileage_600(round(temp_nj(1))+18);

        cycle0_bcn=rated_mileage(round(temp_bcn(1))+18);
        cycle300_bcn=mileage_300(round(temp_bcn(1))+18);
        cycle600_bcn=mileage_600(round(temp_bcn(1))+18);
```

```
        wear_oslo(i)=(cycle0_oslo-cycle300_oslo)/300;
        wear_nj(i)=(cycle0_nj-cycle300_nj)/300;
        wear_bcn(i)=(cycle0_bcn-cycle300_bcn)/300;


        totalwear_oslo=totalwear_oslo+wear_oslo(i);
        totalwear_nj=totalwear_nj+wear_nj(i);
        totalwear_bcn=totalwear_bcn+wear_bcn(i);



        mileage_oslo(i)=rated_mileage(round(temp_oslo(1)+18))-
totalwear_oslo;
        mileage_nj(i)=rated_mileage(round(temp_nj(1)+18))-totalwear_nj;
        mileage_bcn(i)=rated_mileage(round(temp_bcn(1)+18))-
totalwear_bcn;




SOH_oslo(i)=(mileage_oslo(i))/(rated_mileage(round(temp_oslo(1)+18)))*100
;

SOH_nj(i)=(mileage_nj(i))/(rated_mileage(round(temp_nj(1)+18)))*100;

SOH_bcn(i)=(mileage_bcn(i))/(rated_mileage(round(temp_bcn(1)+18)))*100;



    else i>300

        cycle0_oslo=rated_mileage(round(temp_oslo(1))+18);
        cycle300_oslo=mileage_300(round(temp_oslo(1))+18);
        cycle600_oslo=mileage_600(round(temp_oslo(1))+18);

        cycle0_nj=rated_mileage(round(temp_nj(1))+18);
        cycle300_nj=mileage_300(round(temp_nj(1))+18);
        cycle600_nj=mileage_600(round(temp_nj(1))+18);

        cycle0_bcn=rated_mileage(round(temp_bcn(1))+18);
        cycle300_bcn=mileage_300(round(temp_bcn(1))+18);
        cycle600_bcn=mileage_600(round(temp_bcn(1))+18);

        wear_oslo(i)=(cycle300_oslo-cycle600_oslo)/300;
        wear_nj(i)=(cycle300_nj-cycle600_nj)/300;
        wear_bcn(i)=(cycle300_bcn-cycle600_bcn)/300;


        totalwear_oslo=totalwear_oslo+wear_oslo(i);
        totalwear_nj=totalwear_nj+wear_nj(i);
        totalwear_bcn=totalwear_bcn+wear_bcn(i);

        mileage_oslo(i)=rated_mileage(round(temp_oslo(1)+18))-
totalwear_oslo;
```

```
        mileage_nj(i)=rated_mileage(round(temp_nj(1)+18))-totalwear_nj;
        mileage_bcn(i)=rated_mileage(round(temp_bcn(1)+18))-
totalwear_bcn;



SOH_oslo(i)=(mileage_oslo(i))/(rated_mileage(round(temp_oslo(1)+18)))*100
;

SOH_nj(i)=(mileage_nj(i))/(rated_mileage(round(temp_nj(1)+18)))*100;

SOH_bcn(i)=(mileage_bcn(i))/(rated_mileage(round(temp_bcn(1)+18)))*100;


    end

end

plot(N, SOH_oslo, N, SOH_nj, N, SOH_bcn)
title('Battery 3')
xlabel('Number of cycles')
ylabel('SOH (%)')
legend('SOH Oslo','SOH New Jersey','SOH Barcelona')
```