Aging Model for Re-used Electric Vehicle Batteries in Second Life Stationary Applications

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Abstract Energy generation and distribution around the globe expect that micro-grids, renewable and distributed energy services will be key elements in future grid infrastructures. That is why batteries, as storage energy systems, are in the scope of many studies. To counteract the high costs of Li-ion batteries appears the idea of electric vehicle battery reuse or second life for stationary applications. In fact, batteries from electric vehicles are not useful for transportation purposes after they have lost a 20% of its capacity. This study uses an electric equivalent circuit to model battery behavior and aging under five different second life applications: Fast charge of electric vehicles; isolated applications; uninterruptible power systems and Self consumption with and without participation on grid frequency regulation. The battery model takes into account temperature, C-rate, depth of discharge and voltage of the battery to evaluate and calculate battery aging along time and use. This model runs on Matlab and Simulink to determine the battery state of health evolution and, therefore, the rest of useful life, which can be used for future economic analysis and maintenance management.

Keywords Batteries · Second life · Reuse · Model · Aging

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1 Introduction

The majority of sold Electric Vehicles (EV) are equipped with Li-ion batteries to store energy (Gil-Agusti et al. 2014). As it occurs with laptops and other electronic equipment, these batteries degrade with time and use (Broussely et al. 2005). In the automotive sector, these batteries are considered not useful for traction services when they have lost between 20 and 30% of its capacity (Olivares et al. 2013). This is the end of the 1st life and it is also the point where most of the battery aging studies finish (Guenther et al. 2013).

The EV is not profitable without fiscal incentives (Mock and Yang 2014) mostly due to the high costs of batteries, 700 €/kWh. Knowing that the integration of energy storage systems to provide energy services to the electricity grid is being increasingly studied lately (Rastler 2010; Lymperopoulos 2014), car manufacturers try to enhance EV sales by re-selling their batteries at the end of the 1st life. In fact, some 2nd life battery projects already appeared, such as the EVEREST or the Second Life Battery project amongst others. Moreover, many papers and reports presented studies about its economic viability (Gladwin et al. 2013; Viswanathan and Kintner-Meyer 2011) and even some companies were created to work on them, as it is the case of 4R-energy.

All these projects try to demonstrate the technical feasibility of the EV battery re-use to store energy. At the same time, they expect to determine their batteries Rest of Useful Life (RUL) during the 2nd life in order to be able to offer credible guarantees. This last concept, the RUL determination during their 2nd life, is what this study analyzes by means of an equivalent electric circuit model of the battery.

Many authors have extensively studied dynamic battery models. There are simple models using only one resistance (R) and a pair of resistance and capacitor in parallel (RC) (Zhang and Lee 2011; Cho et al. 2012), or more complex models using Change Phase materials and coils (Liu et al. 2011; Osaka et al. 2012). However, the base of these models is the same: the addition of elements into the model incorporate functional particularities and the results accuracy is improved (Guenther et al. 2012).

These models are completed by the addition of the aging effects to determine the RUL under certain current loads. The main factors that accelerate or reduce batteries' aging are: Temperature (T), Depth of discharge (DOD), State of charge (SOC) and intensity rate (C-rate) (Barré et al. 2013; Eddahech 2013; Vetter et al. 2005).

These batteries age either while stored (Calendar aging) or under use (Cycling aging). Regarding the calendar aging, apart from time there are two other factors that participate in the aging of batteries: Temperature and SOC. Temperature effect follows an exponential behavior described by the Arrhenius equation. On the other hand, SOC effect, which may also be implemented using the battery voltage, has a linear effect (Schmalstieg et al. 2014; Delaille et al. 2013).

Cycling aging has two additional parameters to consider: DOD and C-rate (Guena and Leblanc 2006). DOD effect follows a logarithmic relation, while the

C-rate effect is described by a second degree polynomial expression (Lam 2011; Sarasketa-Zabala et al. 2013).

In practice, these relations have two main consequences: An internal resistance increase R_0 and a loss of capacity (Niehoff et al. 2013). Although there are other effects on the RC pairs regarding the instant response of a battery, they are not relevant for RUL estimations and are not implemented in this model.

As the empiric experimentation with batteries for each possible application requires of much time and it is expensive, a battery equivalent electric model parametrized using literature and experimental data from laboratory tests simulates the battery aging. The results of the simulations will provide an illustrative lifespan of batteries under different loads in a fast and economic way.

2 Objective

The main goal of this study is to determine, using an electrochemical model, the estimated lifespan or durability of a battery in different 2nd life applications. These applications are classified in four groups regarding the characteristics of the battery loads.

The estimated RUL will serve to define and program battery replacements and to determine its impact in the amortizations and business cost analysis.

3 Methodology

For the RUL calculation, an electric equivalent circuit model with an R and 4 RC pairs in series will be used, as it is shown in Fig. 1. The OCV element represents a voltage source that establishes the open circuit voltage of a battery in relation to SOC. These parameters are taken from the battery manufacturer datasheet.

Equations 1 and 2 describe the dependencies between the aforementioned calendar and cycling capacity loss and the aging factors.

$$C_{loss\_cal} = f(V, T, t) \tag{1}$$

$$C_{loss\_cyc} = f(I, V, DOD, T, t) \tag{2}$$

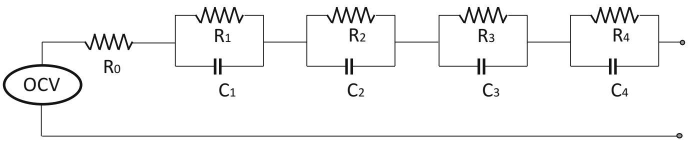

Fig. 1 Electrochemical circuit used, it has a resistance and four RC pairs in series

The calendar capacity fade is mathematically expressed by Eq. 3, which incorporates Temperature, SOC or voltage (V) and time (t) factors.

$$C_{loss\_cal} = (\beta_1 + \beta_2 \cdot V) \times 10^6 \cdot e^{\frac{\beta_3}{T}} \cdot \sqrt{t} \tag{3}$$

On the other hand, the cell cycling capacity fade has, additionally, current (C-rate or I) and DOD factors. In this model, the cycling capacity fade rate is based on the degradation observed under continuous discharge and charge cycles at 1C (being 1C the current intensity corresponding to a complete discharge of a battery in one hour), 273 K, 50% average SOC and 100% DOD. Equations 4–7 adjust the model degradation in relation to the aging factors.

$$I_{ef} = \theta_1 \cdot I^2 + \theta_2 \cdot I + \theta_3 \tag{4}$$

$$V_{ef} = \theta_4 \cdot V + \theta_5 \tag{5}$$

$$DOD_{ef} = \frac{Log_{10}(DOD)}{2} \tag{6}$$

$$T_{ef} = \frac{e^{\frac{\theta_6}{T}}}{e^{\frac{\theta_6}{298}}} \tag{7}$$

Parameters β_1, β_2, β_3, θ_1, θ_2, θ_3, θ_4, θ_5 and θ_6 should be determined for each battery type. Figure 2 presents a graphic representation of these equations in our case.

The electrochemical model runs on MATLAB® and uses Simulink® tools and libraries. Figure 3 presents a block-like schematic representation of the model. The model inputs are the current loads and temperature. These inputs are defined by the 2nd life applications requirements. At their entrance, the model calculates the

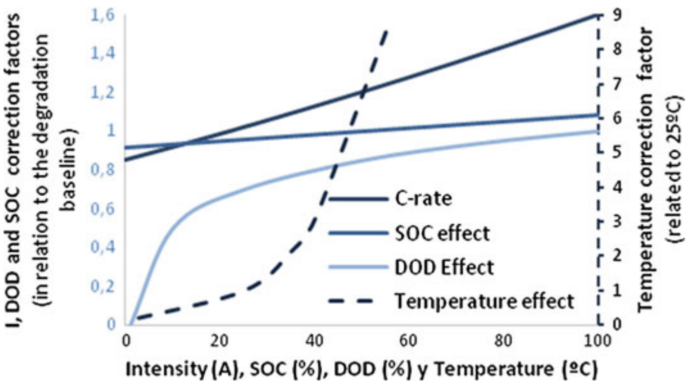

Fig. 2 Effects of the different aging factors in relation to the baseline discharge rate at 25 °C, 1C and 100% DOD cycles

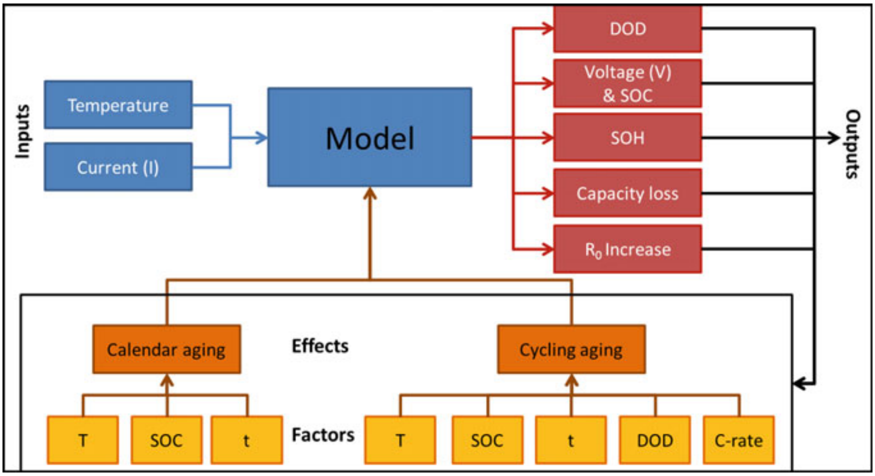

Fig. 3 Block-like schema of the electrochemical model implemented

electric instant response of the battery, providing the following outputs: Voltage (V), SOC and DOD variations, Capacity fade, State of Health (SOH) decrease and internal resistance R_0 increase. These outputs re-enter into the model as feedback or closed loop inputs for the subsequent iterations. This loop is necessary to obtain precise battery aging and performance responses.

Knowing that the main consequences of aging is the capacity loss, the state of health is then calculated as the ratio between the actual battery capacity (Cap) and the initial battery capacity (Cap_{ini}) as it is expressed by Eq. 8. The SOH will be further used to determine the functional end of the second life (Nuhic et al. 2013; Zou et al. 2015).

$$SOH = Cap/Cap_{ini} \tag{8}$$

Moreover, from empirical laboratory tests results, a second order polynomial expression (described by Eq. 9) was obtained relating the SOH with the internal resistance increase (R_0 in the model from Fig. 1). This polynomial relation is consistent compared to other studies with similar conclusions (Dai et al. 2009).

$$R_0 = \alpha_1 + \alpha_2 \cdot SOH + \alpha_3\, SOH^2 \tag{9}$$

This R_0 value determines the battery efficiency degradation and quantifies the energy loss, which is basically caused by Joule effect, expressed by Q[J] in Eq. 10 (Jossen 2006; Braun et al. 2012). Obviously, the energy losses are higher at higher C-rates.

$$Q = R_0 \cdot I^2 \tag{10}$$

To determine the moment when these batteries are not capable to offer the energy that each application needs the model simulates the battery performances under the different use cases and loads, which are:

- Self consumption in residential or commercial environments: These systems are based in the "peak shaving" energy concept. The objective is to reduce the annual electricity bill by storing energy during low tariff hours to use it during high tariff hours and, at the same time, reduce the power tariff contracted. If there are renewable energy systems connected to the micro grid, the storage device can store this energy when the production is higher than the demand. The system load simulation represents a daily full charge and discharge cycle. The average energy consumption in Spanish houses is the energy considered for this simulation, which corresponds to 10 kWh/day.
- Island installations: In this case, as the system is not connected to the electricity grid, the energy storage device should be able to provide energy during the hours when there is no energy production. Additionally, it has to be over-dimensioned in order to ensure electricity power during three days, for the exceptional cases when there cannot be enough energy production (i.e. cloudy days for photovoltaic systems). The same daily energy consumption than in the previous case was considered. Therefore, the energy storage system should have a capacity of 50 kWh. In this use case, the charge and discharge cycles have a 30% DOD.
- EV fast charge: The fast charge of EVs requires power levels near 50 kW. The EV fast charge seriously stress the local network during the first minutes. This effect has been studied by De Hoog et al. (2013), Maitra et al. (2013). An analysis of 2nd life energy storage devices to provide the additional power needed is done to eliminate or delude the stress and to reduce the costs of these high power installations. The 2nd life battery load follows a slow charge and a fast discharge cycle. The battery capacity considered for this application is the same as the one used in the vehicle, that is, 20 kWh. This case assumes two fast EV charges (or cycles) per day.
- Uninterrupted Power Systems (UPS): These type of systems offer energy during around 15 min until the electricity grid power is re-established or other power sources are active. They are often used in telecommunications and data centers, where sudden stops are not conceivable. The battery load cycle follows a slow charge, then the battery system stays completely charged during long periods of time (10 days in this case) and then it suffers a fast discharge. Although the energy capacity of these systems may substantially change from one to another installation, this study case considers only 10 kWh.

Table 1 summarizes the main characteristics of these four applications. It should be emphasized that, for one side, the End of Life (EoL) is reached when the battery SOH decreases to 60% in all applications except for the self-consumption case,

Table 1 Simulation battery 2nd life load cycle characteristics

Application	Initial SOH (%)	Final SOH (%)	Initial DOD (%)	C-rate	Average SOC (%)
Self-consumption	80	40	85	C/20	50
Island	80	60	30	C/75	85
EV fast charge	80	60	85	1.5C	82
UPS	80	60	85	2C	90

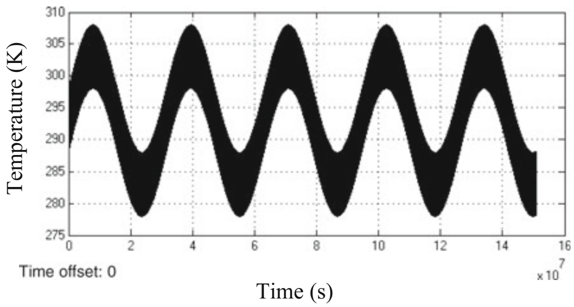

Fig. 4 Annual temperature cycle with ±5 °C daily variations

where it goes until a 40% SOH. In this particular case the capacity loss influences only in the revenue obtained and it is not critical for the normal functionality as it occurs in all other applications. On the other hand, the DOD used for the simulation is 85%, which is the limitation inherited from the EV battery pack for security and safety reasons.

Batteries should be placed under controlled and enclosed environments for the RUL calculations. Hence, the assumption that temperature changes will be soft and away from extreme situations is taken. Accordingly, two possibilities were analyzed in this study: A constant temperature case at 25 °C (298 K) and a temperature year cycle that goes from 10 to 30 °C (283–303 K) with ±5 °C daily variations as it is shown in Fig. 4. The first possibility considers that an active cooling and heating system controls the temperature. The second case has no temperature control. This was done to evaluate if there is a noticeable change in the RUL evolution with or without temperature control. In fact, cooling systems consume energy and cost money, thus, it is preferable to avoid them.

On the economic side, from the results obtained in a previous work (Canals Casals et al. 2014) and from the study by Neubauer et al. (2012) it is considered that reused batteries cost around 100 €/kWh. The battery acquisition cost is obtained by the multiplication of this value and the battery capacity (kWh) needed in each 2nd life application. With this and the simulated RUL results, the minimum amortization costs will be calculated.

4 Results

This section starts with the presentation of the SOH evolution resulting from the simulation at 25 °C constant temperature. The departing SOH is 80%, as this could be the real state of health when batteries leave the vehicle and start their second life. Figure 5 shows, effectively, that the applications with higher C-rates and frequent discharges, like the EV fast charge, age faster. In fact, the battery will last only 1.7 years on EV fast charge applications, while in less demanding applications, like UPS, the battery lifespan is expected to be longer than 24 years. Moreover, the second application with longer lifespan is the island installation, which has low C-rates. Notice that, as it is also appreciable in Fig. 5, the final SOH for self-consumption is 40% and its RUL almost doubles the 60% SOH in comparison.

A deeper analysis of the results shows that the impact of calendar and cycling aging is not constant for all cases. In fact, the calendar degradation becomes more relevant as the battery RUL is longer. This is presented in Fig. 6 by a bar diagram. Accordingly, the UPS and island applications, which are the ones with longer RUL, have a calendar aging impact of 27 and 18% respectively. On the other hand, the applications with less than 10 years' lifespan have a cycling aging impact higher than 95%.

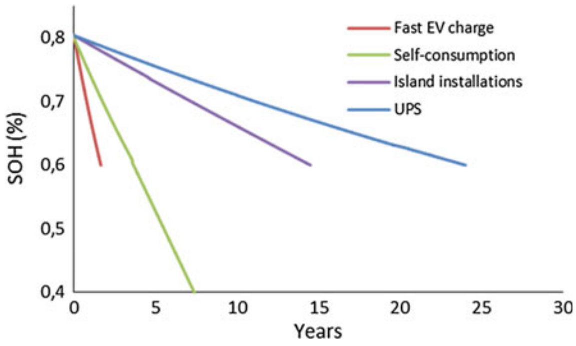

Fig. 5 Battery SOH evolution under different 2nd life applications at 25 °C

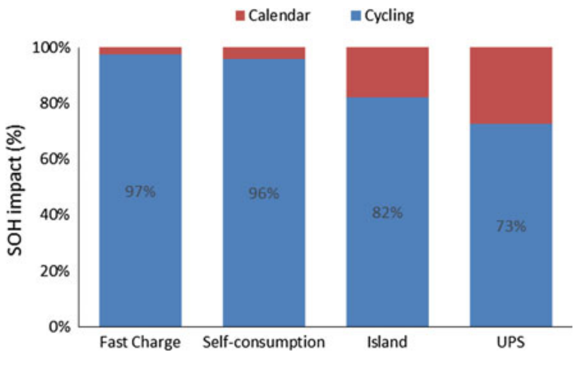

Fig. 6 Impact of the cycling and calendar aging on the final SOH

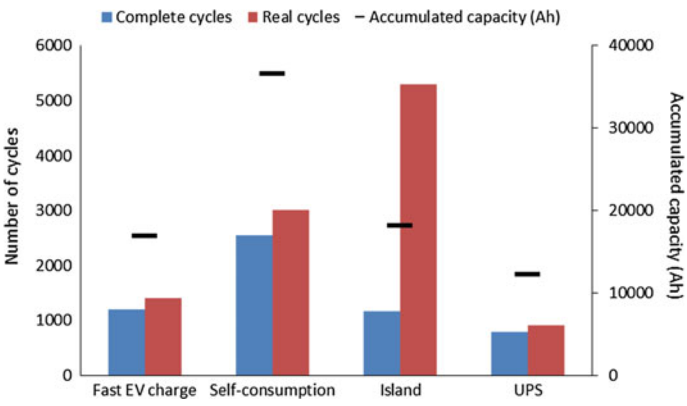

Fig. 7 Number of cycles done per battery and total accumulated capacity discharged on each 2nd life application

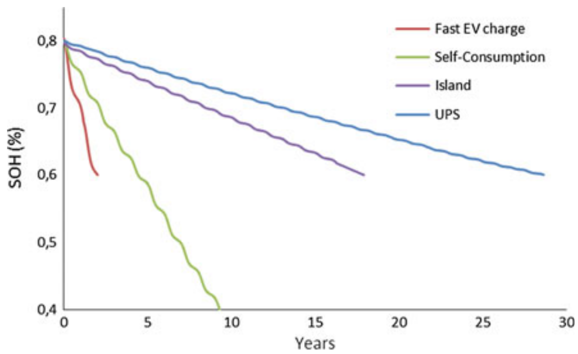

Fig. 8 Battery SOH evolution under different 2nd life applications at variable temperature

The results presented in Fig. 7 allow to identify which is the impact of DOD and C-rate by the quantity of cycles and accumulated capacity exchanged (Ah). The black line in Fig. 7, that represents the total amount of accumulated capacity discharged, shows that the self-consumption application is the one with more energy exchanges. Again, notice that its final SOH is 40% instead of 60%. The UPS application is the one doing fewer cycles and, although being the case with longer lifespan, it is the case having less energy exchanges. Correspondingly, it is the case with lower cycle aging impact, as presented in Fig. 6. The explanation is due, basically, to the battery cycling only during 1.5% of time and resting fully charged afterwards. Additionally, when it finally cycles, it does it under the higher current exigencies studied.

Figure 7 also shows the number of cycles that batteries may do during these 2nd life case studies. Looking carefully to the complete equivalent cycles (which translates the cycles done to 100% DOD cycles), it can be appreciated that self-consumption does 2551 cycles, while others do not achieve 1200 cycles or, in the worse performing case, the UPS finishes after doing only 785 complete cycles.

Using Eq. 9, the final R_0 results indicate that it increases by 74%, reducing significantly the final battery efficiency.

RUL increases around a 20% in all the studied cases when applying a variable temperature cycle. Additionally, the SOH evolution presents a sinusoidal behavior, which corresponds to the annual temperature cycle. Nonetheless, the daily temperature cycle is not appreciable at the presented timescale. Figure 8 shows the obtained results.

The longer lifespan is explained because the working temperature passes more than 2/3 of time below 25 °C. Obviously, if these premises change, the results will change accordingly.

This longer RUL has a direct effect on cost analysis, on maintenance intervention and on investment amortization.

Table 2 reflects the aforementioned economic impact of RUL changes for each application. For example, fast EV charging applications with controlled temperature need to replace batteries in less than 2 years, which implies 1200 €/year in amortization in order to have enough cash to buy new batteries when it is needed. Additionally, Table 2 presents the amortization in relation to the kWh installed, in order to evaluate the costs per energy storage unit.

Additionally, Table 2 allows to compare the obtained results with and without temperature control. Therefore, considering the amortizations all along the battery lifespan, it should be highlighted that their value decreases by the lifespan

Table 2 Results and cost summary

At 25 °C				
	Fast EV charge	Self-consumption	Island	UPS
Endurance (years)	1.7	7.4	14.5	24.0
Minimum capacity of the battery (kWh)	20	10	50	10*
Battery cost (€)	2000	1000	5000	1000
Yearly amortization (€)	1199	135	345	42
Yearly amortization per kWh (€/kWh)	60	14	7	4
No temperature control				
Endurance (years)	2.0	9.3	17.9	28.6
Minimum capacity of the battery (kWh)	20	10	50	10
Battery cost (€)	2000	1000	5000	1000
Yearly amortization (€)	994	107	279	35
Yearly amortization per kWh (€/kWh)	50	11	6	4
Reduction (%)	17	20	19	16

* Notice that, contrarily to other applications, the UPS had a great capacity variability, which goes from phew kWh to MWh. 10 kWh were taken in this study to have a similar order of magnitude with the rest of applications.

enlargement due to the non-controlled temperature cycle between 10 and 30 °C in relation to the 25 °C controlled case. In fact, these reductions may reach the 20% in the best case.

5 Conclusions

The economic viability of using batteries to store energy depends enormously on the battery price and lifespan.

The use of 2nd life batteries allows a reduction on the first aspect, the battery price, being necessary to evaluate the durability of these batteries in stationary applications.

This study showed how the battery lifespan not only depends on the number of cycles but also on the working conditions. Hence, battery lifespan goes from 1.7 years on Fast EV charge applications and almost up to 29 years on UPS applications.

One of the key factors affecting the battery lifespan is temperature. Therefore, it has been observed that the battery life length enlarges a 20% if the temperature oscillates between 10 and 30 °C instead of being controlled and fixed at 25 °C using air cooling systems.

Consequently, there is no need to include active cooling and heating systems in the battery location if it stays within this range of temperatures. This reverts in an important investment reduction (no need to purchase and install any cooling system) and an improvement on efficiency and functional costs as there is no energy use to cool down or heat up the room. In fact, not controlling the room temperature reverts in a reduction between 15 and 20% of the battery amortizations for replacement due to the rest of useful life enlargement.

These aforementioned amortization costs oscillate between the 994 and the 1200 €/year in EV fast charge applications while it reaches only 35–42 €/year in UPS applications. Additionally, self-consumption and island applications require annual amortizations around 120 and 300 € respectively.

Finally, applications with heavier working conditions have lower duration and fewer cycles. Thus, foreseeing optimal results, studies based on oversized systems bringing lower C-rates and DOD should be carried out until the optimum result between initial investments and business revenues is obtained.

The presented battery-aging model allows the evaluation of the expected RUL of batteries under different working conditions in a short period of time and with precision. The RUL results are necessary to evaluate the corresponding business models using energy storage systems.

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