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Ageing aware cell balancing in electric vehicle batteries

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Abstract

A battery pack may be composed of hundreds of individual cells that can evolve differently over their lifespan. Cell performance dispersion could lead to effective battery performance degradation and limit battery lifetime. Classical passive cell balancing systems aim to equalize cell voltages (or states of charge). In this work a passive cell balancing system is controlled to equalize cell capacities over lifespan. This strategy could improve battery lifetime and reduce cell dispersions, facilitating reuse of batteries after their first life.
Keywords: electric vehicle, battery ageing, battery management, cell balancing.

1 Introduction

Electric vehicle batteries are generally composed of tens to hundreds of cells, or even thousands in the case of vehicles like Tesla. These cells are not identical from the moment they are manufactured, through their use and to the end of their life. During manufacturing, tolerances (chemical composition, geometry, temperature, humidity, etc.) mean that no cells are identical. When these cells are packaged to form a battery, their environments differ for every cell: some could be better cooled, others could be heated by adjacent equipments, etc. Moreover, differences in initial conditions (manufacturing) and use conditions (position in a pack) lead to differences in stress causing different individual cell degradations. Therefore, cell capacity dispersion whitin a pack exists from the very beginning of its life and depending of internal and external factors dispersion may increase [1, 2].

Balancing systems are used to overcome the phenomenon of cell imbalance in a pack. Balancing systems are classified in two main families depending of their ability to reuse discharged energy from cells: passive or active balancing. While passive balancing consists simply on discharging some cells of the pack on a resistor (or a transistor acting as a resistor), active balancing gets energy from one or a several cells to restore it to other cells in the pack. For this, active balancing needs a mean to store and convert this energy, many of the active balancing topologies are inspired from CC-CC converter topologies [3, 4]. The most common objective of balancing systems is to get the maximum performances from the battery by equalising cell voltages or SoCs [5, 6] or to get optimal overall performances [7, 8]. Other authors focused in avoiding extreme temperatures and/or SoCs [9–12] to slow down degradations. Finally, some authors consedired directly state of health as the control variable to prolong the battery pack lifetime [13–15]. Other important objective in health balancing could be to equalise battery cell performances at EoL (End of Life). If this is achieved, batteries could be more easily considered for a second life use because of their minimal cell performance dispersion.

In this work, we are investigating the effect of balancing on cell ageing through several basic strategies and scenarios. This study explores the evolution of the performance of the cells composing the battery pack of an electric car in private use. Depending of the strategy, different battery lifetimes and cell dispersions can be observed. Extending lifetime is directly benefic for the cost effectiveness of the battery. Limiting cell dispersion is also a key result of improved balancing strategies, resulting in batteries that are more reliable during their (first) life and easier to use during their second life.

Two scenarios are considered: the first emulates the initial dispersion of cells. The characteristics of cells from production line are not exactly the same. This may be due to manufacturing and environmental differences [16, 17]. Various studies have reported that capacity differences of at least 0.2% and up to 1% can be found between cells from the same production batch [17, 18]. Even under controlled laboratory conditions, these initial dispersions became more pronounced with aging [17].

Second considered scenario was designed to investigate extreme conditions of thermal variation. For this scenario, dispersions in thermal convection and cell internal resistance parameters were considered. Indeed, a number of studies have shown that significant temperature dispersions can occur within a module, sometimes up to 10°C even under normal operating conditions [19–21].

2 Methodology

2.1 Scope of the study

The reference vehicle for this study is an all electric car from BMW, model i3s. This vehicle is equipped with a NMC type battery of 37 kWh. The pack is composed of 118 cells in series. Battery characterization and modelling have been conducted in previous works [22].

A classical usage of the vehicle is considered. A commute to work is made mornings and evenings on weekdays, while longer journeys are envisaged at weekends. WLTC driving cycles are used to represent these travels. With these assumptions, more than 680 km are covered every week. This represents 35 000 km per year.

A full charge (CC phase followed by a CV phase) is done every night.

In this article, we consider a battery pack with dispersions in: initial capacity, resistance and thermal behavior. A normal distribution is considered to affect the cell dispersions. When several dispersions are combined at the same time within the pack, the same cell sees all its characteristics deteriorate, so that, for example, the most vulnerable cell has the lowest initial capacity, the highest resistance and the worst thermal parameters.

2.2 Modelling

VEHLIB, an open source simulation tool is used in this work [23]. For rapid vehicle simulation, quasi-static component models are used. Dynamics and resulting power demand are modeled using a backward approach and a time step of 1s is adopted in simulations. The velocity as a function of time is known in advance and this driving cycle corresponds to a necessary torque at the wheels to overcome the inertia of the vehicle as well as the resistive forces acting on it. The mechanical transmission components have constant efficiencies. Typical efficiency maps are used to model the electric machine and its converter.

The battery model is composed of three sub-models: electric, thermal and ageing. The chosen electric model is an ideal voltage source (OCV) with a series resistance (R). Both parameters depend of T and SoC, with SoC calculated by current integration. The battery pack thermal behaviour is obtained with a 0D model for each cell. Finally, for the ageing model, Eyring laws are used as in [24].

Notice that every single cell in the pack is individually simulated in VEHLIB. Every parameter (electrical, thermal, ageing) can be individualised to represent the intrinsic characteristics of each cell (performances, environment, state). Although this adds a certain degree of complexity, this choice allows great flexibility when it comes to studying the differences in cell behaviour within the pack.

A passive balancing consisting in a resistor is controlled by an ideal switch on each cell. Switches can be enabled or disabled depending of cell balancing strategy. Chosen resistor value is 0.5 Ohm to allow relatively fast actions on each cell SoC. As the cell nominal capacity is 94Ah, and their voltage generally between 4 and 3V, this resistance value implies a current between C/12 and C/16. This allows, for example, to discharge a cell by 10% in around 1.5 hours.

2.3 Cell balancing strategies

2.3.1 Classical strategy

The classical cell balancing strategy consists of a cell voltage equalization during the CV phase of the charge. The balancing switch of a cell is enabled when its voltage is higher than the mean cell voltage of the pack.

2.3.2 Improved strategy

In our study, the lever for modifying cell ageing in a pack is the state-of-charge level. Therefore, to protect the weakest cells, we need to reduce their state of charge. As a consequence, the amount of available energy in the pack decreases and this strategy can be adopted only when vehicle autonomy is not an issue, i.e. during the week days. K-means clustering is used to make 2 populations of cells depending on their current capacities. The cluster with the lowest capacity is then discharged by closing the balancing switch during the CV phases. The maximum difference in state of charge amplitude in the cells of the pack is a parameter of the simulations. This strategy is declined in two levels allowing up to 10 and 20% (namely improved strategy 1 and 2) cell SoC differences whithin the pack.

When the week-end arrives, more energy is needed and the strategy switch to equalize the state of charge of the different cells. Technically, 2 populations are identified based on their cell voltages. The shunts of the highest population are closed during CV phase. The process is stopped when dispersion in cell voltage is less than 10 mV.

An illustration of the behavior over a week is presented in figure 1: from Monday to Friday, the strategy causes the states of charge of the cells to diverge in such a way as to set lower states of charge to the cells with the lowest capacity. From the Friday evening charge onwards, the states of charge are equalised again to allow maximum range during weekend journeys.

3 Results

3.1 First scenario: manufacturing dispersion

First scenario is used to study the influence of initial capacity dispersions on ageing depending of different balancing strategies: classical strategy, improved strategies 1 and 2.

As explained in the introduction, differences in capacity appear from the cell manufacturing stage. In our simulation framework, initial capacity dispersion at the beginning of life (ΔQ_{BoL}) can be included. Following this parameter, all the cell capacities will be spread according to a truncated normal distribution of amplitude ΔQ_{BoL} (in % of median value).

As mentioned above, improved strategies differ from the classical one. Whereas the traditional approach is to equalise the cell voltages or SoCs, our balancing approach is to balance the cell capacity values (Ah). For each strategy, use case described above is simulated considering a battery pack with a cell capacity dispersion of 1%. All other parameters of battery cells are identical (impedances, thermal, ageing law parameters, etc.). Ambient temperature is set to 40°C to accelerate simulations.

Both balancing strategies do not allow to prolong battery lifetime significantly (+0.6 and +1.4% respectively) compared to base strategy (table 1). However, both strategies succeed to rapidly equalise cell capacities. As shown in Figure 2, cell capacities converge and capacity equalisation is almost perfect when the improved strategy is used. At End of Life (EoL), cell capacity dispersion is 1.04, 0.08 and 0.09% for classical balancing, improved strategies 1 and 2 respectively. Other values of initial capacity dispersion (2, 3, and 6%) have been tested with similar behaviours.

We can conclude that under this scenario the main advantage of improved strategies is not to gain in lifespan, but to make the pack more uniform at End of Life.

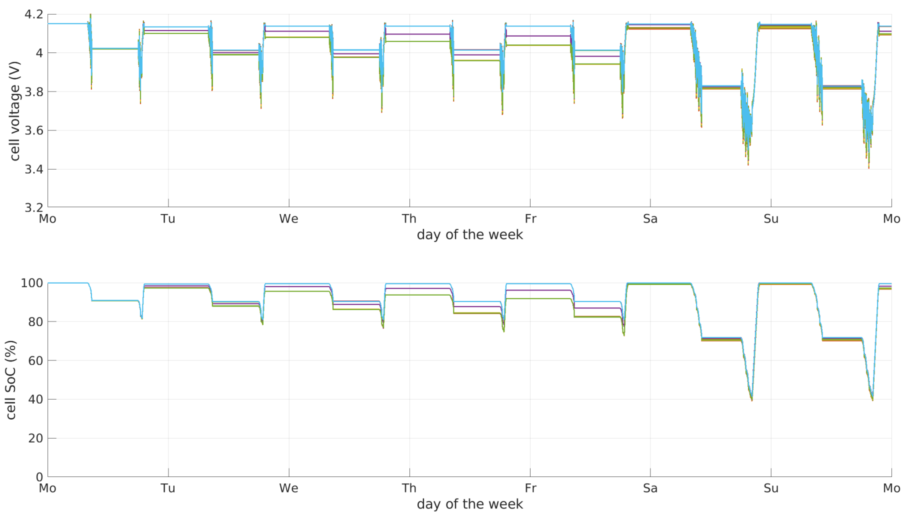

Figure 1: Cell voltage and soc evolution during a week, second scenario, improved strategy 1.

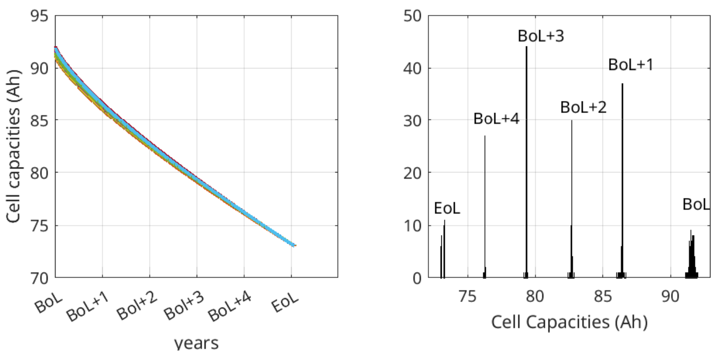

Figure 2: Cell capacity evolution and capacity dispersions in base scenario, improved strategy 1.

Scenario	Lifetime in days (+% life gain)			ΔQ_{EoL} (%)		
	classical	improved 1	improved 2	classical	improved 1	improved 2
Manufacturing	1803	1814 (+0.6%)	1829 (+1.4%)	1.04	0.08	0.09
Thermal	1463	1553 (+6,2%)	1725 (+17,9%)	4.74	3.67	1.71

Table 1: Lifetime (days), lifetime gain (%) and End of Life capacity dispersion (ΔQ_{EoL}) for different balancing strategies in both scenarios with initial capacity dispersion of 1%.

3.2 Second scenario: thermal behaviour dispersion

In this scenario the same use case and balancing strategies mentioned above are studied, but now by considering a battery pack with dispersion of cells in terms of ΔQ_{BoL}, internal resistance and thermal convection. A extreme case of dispersion has been chosen to explore the limits of these balancing strategies: internal resistance dispersion is set to 100% and convection dispersion is set to 80%. Same simulations with ΔQ_{BoL} from 1 to 6% and three balancing strategies have been performed.

In this case, gain in lifetime compared with the classical balancing strategy is clear: 6 to 7% for improved strategy 1 and 16 to 18% for improved strategy 2. On the other hand, in this scenario, no balancing strategy was able to reduce cell capacity dispersion. However, again, improved strategies keep lower values of dispersion compared to the classical balancing strategy. For example, with ΔQ_{BoL} of 1%, classical balancing strategy ΔQ_{EoL} is 4.74% while improved strategies 1 and 2 obtain 3.67 and 1.71% respectively.

We can conclude that under this scenario the main advantage of improved strategies is to gain in lifespan, but cell capacity dispersion will always grow during lifespan.

4 Discussion

In this work, we explored the possibility of using a passive balancing system. As explained in the introduction, conventional balancing strategies consist in equalizing the voltage or the SoC. Other strategies reported in the literature consider energy optimization. These strategies fail to compensate cell dispersions, either initial or environmental, which will result in non-uniform battery ageing. Finally, other strategies avoiding extreme temperatures will have a limited effect in cases where temperature dispersion cannot be countered by reducing the load on certain cells.

The strategy considered in this work is to use the individual state of charge of the cells to control their aging, allowing the most degraded cells to operate at lower SoC levels. This strategy produced noticeable but different results in both considered scenarios.

In the first "manufacturing" scenario the cells have an initial capacity dispersion of 1%. The conventional voltage balancing strategy led to end of life in 1803 days, and the capacity dispersion remained almost constant (1.04% at end of life). Our strategy did not led to a substantial gain in longevity, but the cells reached end of life with a very low dispersion (<0.1%), allowing the battery to be used for a second life with no need of reconditioning cells.

In the second "thermal" scenario, where thermal gradients are extreme, the conventional voltage balancing strategy led to aging in 1463 days and capacity dispersion of 4.74%. Our strategy enabled a substantial gain in longevity (up to +17.9%) and -to a certain extent- limited capacity dispersion.

In both scenarios, longer lifetime and lower cell dispersions are obtained in improved strategy compared to classical strategy. These two scenarios are extremes in relation to actual battery use. Real scenarios will be at intermediate states of dispersion of each parameter, for instance, individual capacity or thermal gradients. This leads us to conclude that the improved strategy will in all cases improve service life and limit dispersion compared with the conventional balancing strategy.

5 Conclusions

In this paper we have presented a simulation study of the possibilities of balancing the capacities of the cells in a battery pack. This strategy differs from the conventional strategy of balancing the voltage and/or the SoC.

A simulation framework based on the VEHLIB library has been developed enabling to carry out complex simulation sequences combining vehicle use, rest and battery charge phases. During charges, we implemented several passive balancing strategies. This framework allows us to simulate a wide range of possibilities and in this work we focused on the dispersion of the characteristics of the cells in the pack.

We studied two scenarios, the first considering only a difference in initial capacity (from 1 to 6%) and the second considering in addition extreme dispersions of internal resistance (100%) and convection (80%). Depending on the scenario, gains in lifetime and reductions in cell capacity dispersion are observed. However, the results are very contrasted: while the gains in lifetime are low for the first scenario (less than 2%), they are very high for the second (up to 18%). On the contrary, in the first scenario cell equalisation is almost perfect (to 0.1% in some cases) whereas the extreme dispersion scenario does not allow us to reduce the initial dispersion, even though this dispersion is always smaller with the improved balancing strategies than with the classical strategy.

Further works could consist in conducting a sensitivity analysis to examine the effects of each model parameter on balancing strategies, including in this analysis intrinsic ageing differences (initial ageing, ageing rate) of cells. This study could be used as a basis to develop intelligent balancing strategies improving the long term operation of the battery in terms of economical and ecological costs. The results of this study may be validated real use data, for example from Grid4Mobility project.

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Presenter Biography

Eduardo Redondo-Iglesias was born in Vigo, Spain, in 1981. In 2009, he joined Université Gustave Eiffel (formerly IFSTTAR) in Bron, France. In 2017 he received the Ph.D. degree in Electrical Engineering from the University of Lyon (France) after the successful defence of his thesis entitled *Study of lithium-ion batteries ageing in electric vehicle applications: Calendar and cycling ageing combination effects*. His research activities are electrical modelling and characterisation of batteries and their ageing.