A BATTERY TESTING TOOLBOX FOR REAL-WORLD OPERATING CONDITIONS

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ABSTRACT

Battery energy storage systems are being deployed at a high pace to accommodate the integration of renewable energy. Most systems are targeted to stay operational for a decade. As a result degradation information is crucial for most of the battery storage projects. As ageing depends on the operating conditions of the battery, it is necessary to characterize the battery over time. Although tracking of battery cell degradation is extensively done under lab conditions, the challenge today lies in the online assessment of battery ageing. Classically, the battery must be taken out of operation to perform the characterization. ENGIE Laborelec is studying how on-the-field characterization methods could be used without stopping the battery operation.

INTRODUCTION

Ageing is of crucial importance for economical and safety reasons, especially for 10 years grid scale storage projects. There are different methods available to assess ageing of Li-ion battery cells, but there is only limited experience with the performance and life-time expectancy of complete systems. In its monitoring approach based on in-field characterisation methods, ENGIE Laborelec proposes to answer the following questions: is the battery evolving like expected and what modifications to use-case or battery are needed to meet the life-time of the project? How to report most efficiently?

AVAILABLE METHODS

Besides the development of an ageing model (together with Aachen University), we apply an "online" monitoring methodology, that brings complementary information compared to what an integrator proposes. Online means that the methodology makes use of the measurements during the normal operation of the battery. Depending on the parameter wanted (capacity, resistance,..), specific time intervals are automatically selected (sliced) from the measurements and combined into a "standard test" sequence. This test sequence can be repeated during the life-time of the project and thus give insights in the health and degradation of the battery.

ENGIE Laborelec selected specific methods for the online monitoring, usually applied at cell level, but tested here at battery system level. These methods are defined in the following chapters.

Incremental capacity analysis

The incremental capacity analysis (ICA) is a well-known method to study lithium-ion battery degradation mechanisms and consequently, it is used to follow the capacity fading process and evaluate the battery state-of-health (SoH). Its description is based on the reference [1]. Incremental capacity is calculated by differentiating the change in battery capacity (dQ) to the change in terminal voltage (dV) during either charging or discharging.
The voltage plateaus on the charging/discharging curve can be transformed into clearly identifiable peaks on the dQ/dV curve. Each peak in this curve is related to a specific electrochemical reaction and can be characterized by an intensity, an area and a position.

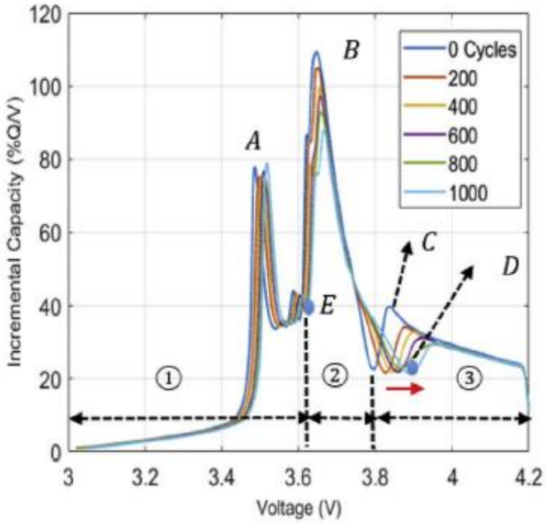


Figure 1: Charging ICA curves at different cell ages [1]

By analyzing the change of peak intensity, area or position throughout ageing, relationships can be found with the battery capacity.
Like represented in Figure 1, different peaks can be identified in the dQ/dV curve. These peaks appear at different states of charge, enabling the possibility to make

the dQ/dV analysis on limited (dis)charging curve sections. Indeed, during operation, the battery is not necessarily operated within the full available SoC range, but can undergo limited SoC variations.

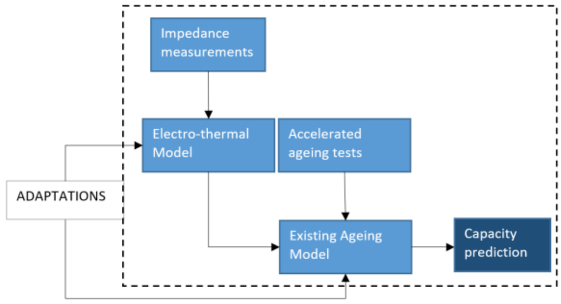
Internal resistance analysis

In addition to capacity degradation the relative evolution of the internal resistance of a battery cell is correlated to its performance (meaning capacity degradation, loss of power capability). Knowing that most degradation mechanisms in Li-Ion batteries alter the particle and/or electrode structure it comes as no surprise that the internal electrical impedance is affected by this degradation process. As a result, the evolution of the internal cell impedance can be used to assess the SoH of the battery. The internal impedance of a battery cell, however, is a complex impedance which would require characterisation at different frequencies to determine fully. Furthermore the complex impedance of a Li-Ion battery cell is dependant of its SoC. When developing an online SoH estimation, based on impedance estimations, this would require the exact knowledge of the SoC. The latter two difficulties can be overcome given that the impedance at certain frequency ranges is almost completely independent of the SoC and is more sensitive to associated degradation mechanisms at these frequencies, which allows for a targeted impedance measurement. [3]

Ageing modelling

The two above methods describe calculations that can be performed on field data to get information about ageing. This paragraph presents the determination of ageing by modelling the evolution of the capacity with time using basic battery load profile information (I, U, T). ENGIE Laborelec worked in collaboration with RWTH Aachen to adapt the existing ageing model for other kinds of cells than the ones (Sanyo UR18650E, NMC-Graphite) used by Aachen to derive ageing equations. The method is well described in [2], but is summarized here below.

- RWTH Aachen performed several tests on cells varying the parameters that have an impact on ageing (Depth of Discharge, temperature, voltage, …), with the aim to derive calendar and cycle ageing equations. These equations are the basis of the ageing model.
- A load profile for a cell is generally limited to a current or power command. To translate this into parameters affecting ageing, an electrical-thermal model is required. This model is parametrized through impedance spectroscopy measurements.



This model enables to determine how specific cells will age when submitted to certain load and temperature profiles. The validation of the model outputs is done by comparing available field data on capacity. If quality data is available, an online capacity estimation method can also be used, based on data obtained during relaxation phases of the battery.

MONITORED STORAGE PLANTS

The idea of the developed work is to use the tools presented above, usually applied on battery cells, on battery system data and then on field data. The field data selected for the monitoring come from different storage plants: 7MW-6.3 MWh storage park used for frequency control regulation (FCR), a residential battery used for solar energy storage, 2nd life electrical vehicle (EV) battery used in a stationary application (FCR), 6MW-6MWh storage plant for the storage of solar energy.

APPLICATION OF THE METHODS ON FIELD DATA

In this chapter, the results of the application of the different methods on field data will be reported.

Incremental capacity analysis

We extend the SoH monitoring approach based on IC peak tracking from single cells to battery modules/packs, also by selecting specific time intervals in (dis)charge.

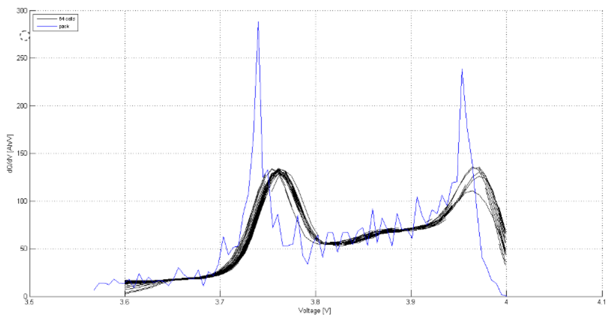


Figure 2: IC curves of a EV battery pack (blue line), with IC curves of 64 cells inside the pack (black lines)

Figure 2 compares the IC curve of a 2nd life EV battery pack, together with the IC curves of the individual cells

constituting the battery pack.
We observe that the IC curve of the pack shows a rather similar fingerprint that could be tracked throughout the pack life as accessible ageing indication.

Internal resistance analysis

Based on this principle an internal resistance estimation algorithm was developed allowing the estimation of the internal resistance at the relevant frequency. A result is shown in Figure 3 where this algorithm is applied on real-time data acquired from the BMS. The system under study was a commercial available battery module of 3.3kWh with an operating voltage in the range of 42 to 58.8V.

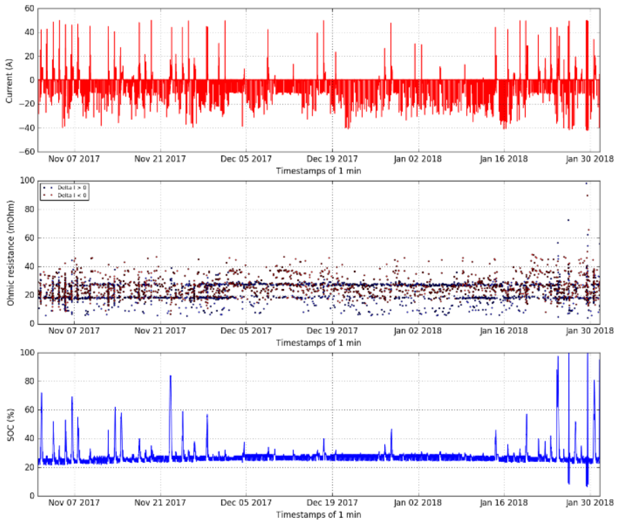


Figure 3: Example of resistance estimation on during operation of a battery module. Top: current through the battery module, middle: estimated resistance, bottom: SoC of the battery.

As one can see in the middle plot of figure 3 there is still a great variability in the estimated internal resistance. This is mainly due to the fact that real-life battery data assed by a BMS is less accurate and has a higher sampling rate then battery testers used in the lab. The variability of the estimated resistance can however be increased by applying the proper filters. This is part of ongoing developments.

Ageing modelling

The model developed by RWTH Aachen has been used on the renewable energy storage plant. It has been adapted (cells type, battery configuration) to determine the capacity decrease with time.
The output of the model (expressed in percentage of the initial capacity) has been compared to the SoH values given by the BMS. On the graph below, we can see the remaining capacity of 90 battery modules present in one battery system. The remaining capacity has been estimated for each module, based on preliminary temperature, voltage, current information.

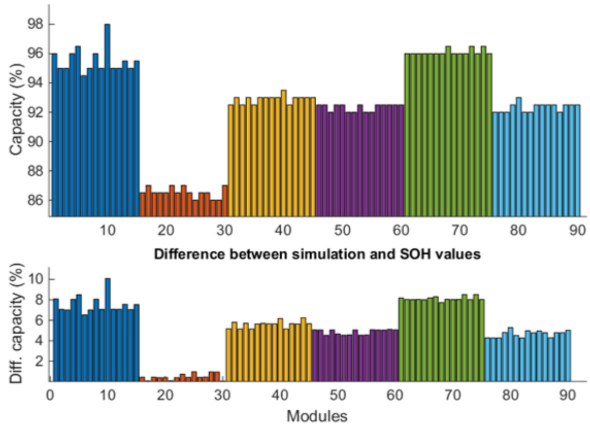


Figure 4: Model output expressed in % of initial capacity, and difference compared with the SoH given by the battery BMS

These first results should be validated either by a capacity measurement in the field, before further regression of the model, or estimated by looking at specific relaxation phases in the battery operation. The results obtained with this latter method are given for illustration and indication.
Figure 5 shows the operation moments that have to be detected and taken into account to determine relaxation phases.

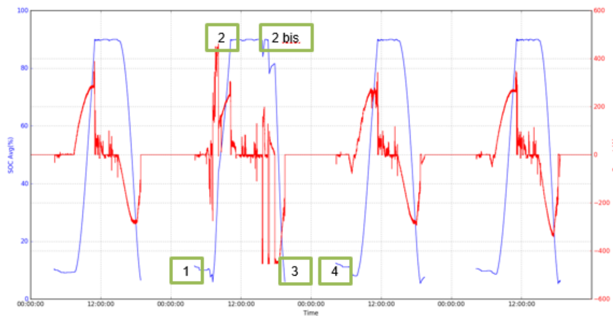


Figure 5: Points 1, 2, 2bis, 3 and 4 have to be automatically detected to be used in the calculation function of the relaxation phases

Figure 6 shows the SoH indication given by the BMS (green line) and the capacity calculated (blue dots) by choosing specific relaxation moments in the current and SoC profiles for one pack of the energy storage plant. The precision of this method depends on the available data quality.
Although there is, in this case, a consequent difference between both results, they evolve on the same manner and the calculated values give indications to be taken as yearly reference values.

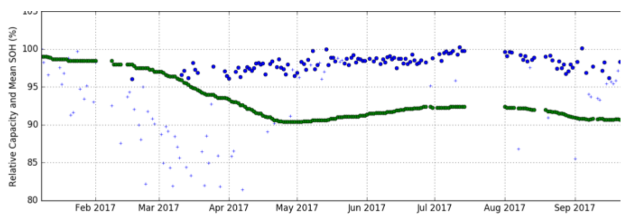


Figure 6: BMS indication of the SoH evolution of one pack of the solar storage plant (green line) compared to the estimated capacity (% of initial installed capacity)

In the next steps, the model will be used for the storage plant used for FCR application. For this specific project a comparison of field-based analysis with lab results on the cell will be possible and will be systematically performed, enabling to understand the impact of measurement granularities and uncertainties

WEB REPORTING

DATA GATHERING AND REPORTING PROCESS

At ENGIE Laborelec we use an "online" monitoring methodology that is complementary to what an integrator proposes and that helps the owner better understand how his battery is performing and what he can expect in the coming years.
The monitoring system can be split up in 3 phases: data collection, data treatment and a user interface towards the experts and clients.

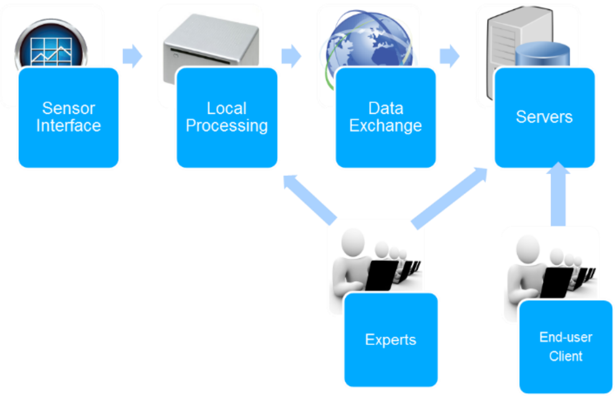


Figure 7: Data gathering and reporting process

Data collection

For the data collection, the system is very open and can be customized to the situation of the client. For battery projects in- and outside the ENGIE group, different IT policies and restrictions apply, needing a very open approach. Furthermore, every integrator has his way of working meaning that the fleet of batteries is very heterogeneous, even within ENGIE. At the design phase of a project, it is crucial to define requirements for the data collection so that this doesn't become a very complex matter once the project is running.
For demonstration purposes, the system can also be used with data dumps (offline data files).
Finally, the data is stored in a Historian server in the cloud where it can further be processed.

Data treatment

The data treatment can be divided into two types of analyses: short- and long-term.
Short-term data treatment focusses on (quasi) real-time deviations or information from the battery. This is similar to a dashboard provided by the integrator.
The long-term analysis is the core service that is offered by the monitoring system. The methods to perform this analysis are presented in the previous paragraphs.
All calculations are implemented in the Python environment.

User interface

The main focus for the development of the user interface was simplicity. While the complexity of the calculations is implemented in the back-office, the user interface should provide the owner or manager of the battery asset a high-level view on the health and correct functioning of the system.
The interface contains a list of topics that are being monitored with a simple OK / NOT OK and a short comment whenever useful. For those interested in more details it is possible to *click through* to see related charts and trends in the page.

Figure 8: User interface detailed view

CONCLUSION

Useful information (for battery ageing information) in the battery operation profile could be extracted from field data without taking the battery out of operation.
Cell capacity determination or cell characterization methods have been applied to battery systems and show some similarity with ageing information gathered at cell level.

This encourages us to continue applying online monitoring calculations to get live ageing information on battery systems.

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