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Online and BMS implementable SoH estimation for Lithium ion battery packs

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Summary

Accurate on board State of Health (SoH) estimation is a crucial parameter that needs to be calculated in order to keep the battery pack safe and under control. The Battery Management System (BMS) takes charge of many functionalities: among others, it diagnoses the different states of the battery, monitors the measurable parameters and manages the battery pack electrically and thermally. All these functionalities are integrated into algorithms or estimating techniques and have to be implemented in a microcontroller. This device is required to be powerful enough for performing all the computational effort for the algorithms at the lowest possible cost, in order to make cost-effective and versatile BMS's. The objective of this work is to develop a SoH estimation technique which covers all these requirements. Nevertheless, highly accurate results have been achieved with a method based on the study of the incremental capacity curves. As a result, an implementable and accurate online algorithm has been developed for NMC/Graphite battery packs estimating the SoH within an error less than 2%.

Keywords: Battery Management System, State of Health, Incremental Capacity, NMC/Graphite.

1 Introduction

The need of safe and long life energy storage systems used in battery powered applications is currently rapidly growing. Unfortunately, there is still many research to do on how batteries degrade and how energy and power capabilities reduce. SoH estimation is a key parameter in order to follow the life state of the battery. Its accurate estimation can prevent failures and risky situations regarding the battery.

There are many techniques, algorithms and models specifically developed for SoH estimation. State of the art reviews like [1–3] reflect that the methods accomplished until the moment do not fulfill all the requirements an online and accurate SoH estimation needs. Particularly in [1] the studied methods are categorized in two groups, adaptive methods and experimental techniques as shown in table 1. It is highlighted that in general experimental techniques require a low computational effort which makes them able to be implemented online. In general, their accuracy is not high enough so not very reliable results are obtained. On the contrary, adaptive methods do reach very accurate estimations, but at the same time requiring high computational loads. From this scenario, a new estimation path is introduced through the use of differential electrochemical analyses.

There are two possibilities of using and plotting the differential electrochemical analyses, differential voltage curves or incremental capacity curves. For this specific work incremental capacity (IC) curves are going to be deeply studied. Three NMC/Graphite cells have been tested along their life and from their obtained IC curves, a novel and accurate algorithm has been developed. Not only at cell level but also at battery pack level the algorithm has been tested and validated showing high accurate results obtaining always lower errors than 2%.

Table 1: Differences between experimental techniques and adaptive methods [1].

	SoH Estimation	
	Experimental techniques	Adaptive methods
Based on	Storing the lifetime data and the use of the previous knowledge of the operation performance of the cell/battery	Calculation of the parameters, which are sensitive to the degradation in a cell/battery
Advantages	- Low computational effort - Possible implementation in a BMS	- High accuracy - Possible to be used as in situ estimation
Drawbacks	- Low accuracy - Not suited for in situ estimation	- High computational effort - Difficult in BMS implementation

In this regard, this study presents a complete explanation and validation regarding the developed SoH estimation algorithm valid at battery pack level. The paper is arranged as follows: Section two introduces the tested cells and discusses the incremental capacity curves which are going to be used along the research. Section 3 and 4 present the obtained experimental results first at cell level and after at module and battery pack level. To finish, section 5 presents the main conclusions.

2 Experimental

2.1 Cycling

Three 40Ah graphite (G) based anode and $LiNi_{1-xy}Mn_yCo_xO_2$ (NMC) based cathode lithium-ion cells were tested along their useful life. From the beginning of life (BoL) until their end of life (EoL) which in this case was defined as 20% capacity loss, if reached. The three cells were tested in a controllable environment of 25ºC, cycled at 1C charge and discharge current, and at different depths of discharge (DoD). The cells were cycled at 80%, 60% and 30% DoDs. With the purpose of testing the three cells at the same way, every 100 cycles two different tests were performed, a capacity test at 1C current rate and a full charge and discharge operated at C/5. The SoH was estimated from the ratio of the discharged capacity over the initial one as presented by equation (1).

$$SoH = \frac{Q_{Aged\ Battery}}{Q_{Fresch\ Battery}} \times 100\% \quad (1)$$

2.2 Incremental capacity curves

Differential electrochemical analyses have been widely used for the detection of aging and degradation mechanisms [4-10]. Therefore, its use for SoH estimation might be very beneficial. Along this work incremental capacity curves, *dQ/dV f(V)* are going to be used. Concretely these curves have already been used for aging estimation and degradation mechanisms detection. In fact, different battery technologies have been studied by the use of IC curves: LFP cells [4–6], LTO batteries [7], LCO [8] and NMC [9,10]. SoH estimation has also been studied by applying this technique in different battery technologies, like for NMC cells [11–13], LFP [14–16] and also composites NMC+LMO [16] cells.

3 Results

3.1 Cycling

As mentioned the cells have been tested at different DoDs but following the same testing conditions and protocol performance. Cell A refers to the cell cycled at 80% DoD. This cell reached a state close to the EoL state, nearly reaching 80% of its initial capacity, at the end of the experiment. On the contrary, the rest of the cells do not reach the EoL state, due to time constraints. Cell B corresponds to the cell tested at 60% DoD. This cell reached 95% of its initial capacity. Finally cell C was cycled at 30% DoD up to a 90% SoH. Figure 1 shows the evolution of the IC curves from the tested cells in terms of aging, from the BoL until a 84.7% state. These curves are going to be used as the base for the SoH estimation technique to be developed.

The plotted IC curves show a clear evolution as the cells degrade (figure 1), regardless the DoD in which they have been cycled. From the shape of the obtained curves, four features could be selected in order to develop a reliable estimation of battery life: three peaks and one shoulder. The 3 peaks have their initial maximum of intensity at 3.65 V (a), 3.55 V (b) and 3.45 V (c). As they degrade, their maximum of intensity shifts towards lower potentials and less potentials The shoulder is located between 3.8 V and 4.0 V (d) and as the cell degrades its intensity decreases. [17].

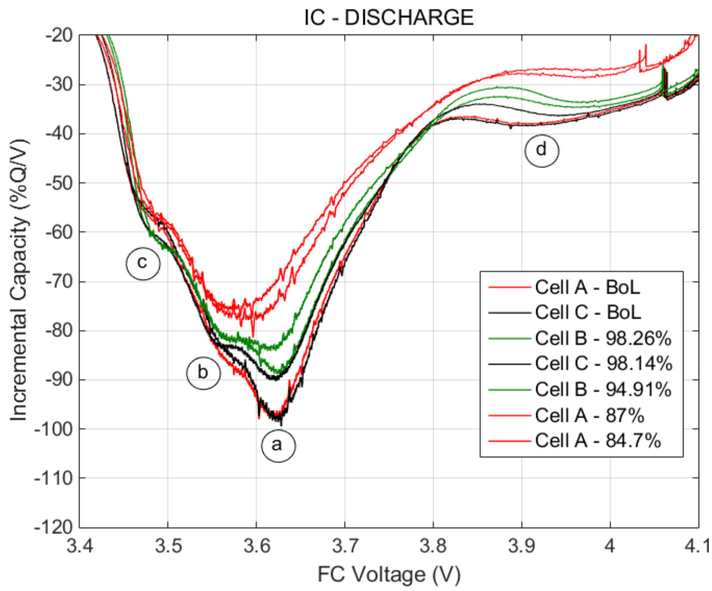

Figure 1: Evolution of IC curves obtained from the tested cells in terms of aging.

3.2 Features of interests

The developed BMS algorithm has its basis on our previous published work "Online State of Health estimation on NMC cells based on Predictive Analytics" [17]. In [17], the same Graphite/NMC cells were tested in order to obtain efficient and useful ageing patterns. In this research, both curves were used; DV and IC curves. For the IC curves, 4 features of interests (FoI) were selected, the DV curves on the contrary, were determined by 6 FoIs.

So as to estimate the SoH, three techniques were tested: Ordinary Least Squares (OLS), Multilayer Perceptron (MLP) and Support Vector Machine (SVM). The first technique, although simple in nature, provides an easily interpretable understanding of the linear relationship of the predictors and the target variable. Both MLP and SVM have been selected because they are state-of-the-art in their field and have been used extensively before in other studies. These techniques can additionally capture nonlinear relationships and as such are potentially more accurate and versatile in capturing relations between predictors and the target variable. On the other hand, these techniques result in a black box model which does not allow interpretation of the modeled relations. As figure 2 shows, the three techniques employed on the datasets predict the SoH of batteries in a highly accurate way [17].

Results coming from neural network estimation demonstrated a slight advantage, but the complexity of the technique might not made it a worthwhile choice. Table 2 shows a basic summary of the obtained results. The takeaway of this experiment was to show that it is possible to estimate the health of batteries accurately based on the FoIS selected from the IC and DV curves [17].

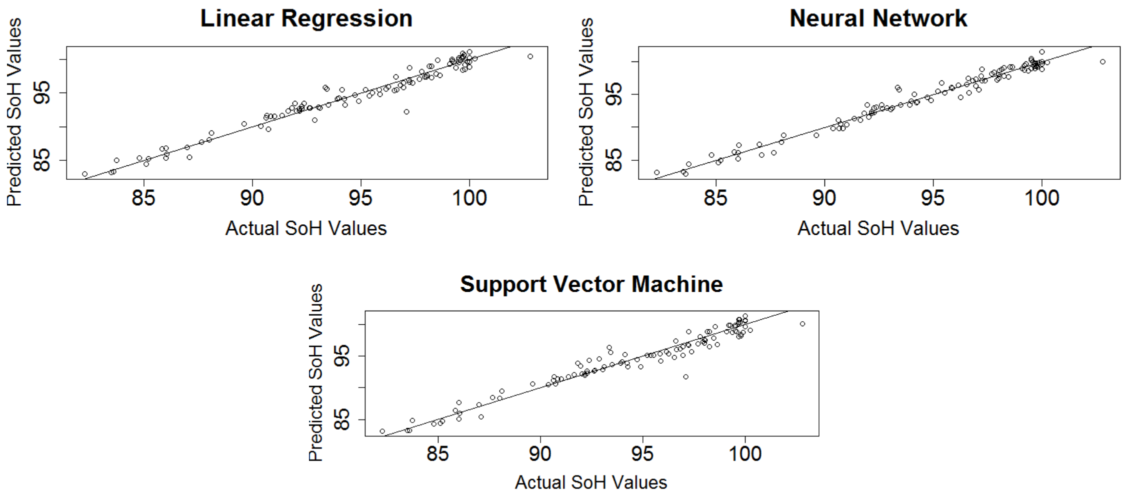

Figure 2: Visual representation of the actual values plotted against the predicted values. The solid line represents x=y. The closer towards the solid line, the smaller the difference between the actual and predicted value [17].

Table 2: Summary table of the experiments. All techniques performed remarkably well in terms of accuracy with the neural network having a slight edge over the other two techniques. However in terms of comprehensibility the linear regression is more preferred as the two techniques act more as a 'Black Box'[17].

	Linear Regression	Neural Network	Support Vector Machine
Accuracy	Very Accurate	Most Accurate	Very Accurate
Comprehensibility	Very Comprehensible	'Black Box'	'Black Box'

The algorithm to be developed aims to be as light and fast as possible, in order to be able to be implemented in a BMS. Accordingly, the two peaks located at the lowest voltage positions will not be taken into consideration for the algorithm development. Moreover, in this research only the IC curves are tested and the number of used FoIs is decreased down to 3, considering in this case features (a) and (d). For the feature (a) located at 3.65V, both references will be considered, voltage and incremental capacity values.

Figures 3 and 4 represent the feature selection, which is going to be considered in order to build the estimation technique at both cases, through charging (figure 3) and discharging (figure 4). Both testing ways are going to be considered in order to develop the algorithm in both ways, so that the one, which fits better the application can be used.

Not to confuse the first general feature selection (a-b-c-d) with the actual one, nomenclature will be changed to 1-2-3 for the features selection used for the online algorithm. FoIs ① and ② correspond to the reached maximum intensity and voltage position of the most intense electrochemical feature around 3.65 V. This peak voltage shifted and its absolute maximum intensity decreased with aging. According to cell emulation results, this peak maximum intensity and position are influenced mainly by the loss of lithium inventory [17]. FoI ③ was defined as the IC intensity at 4 V and is directly proportional to the loss of active material on the positive electrode (PE) [17].

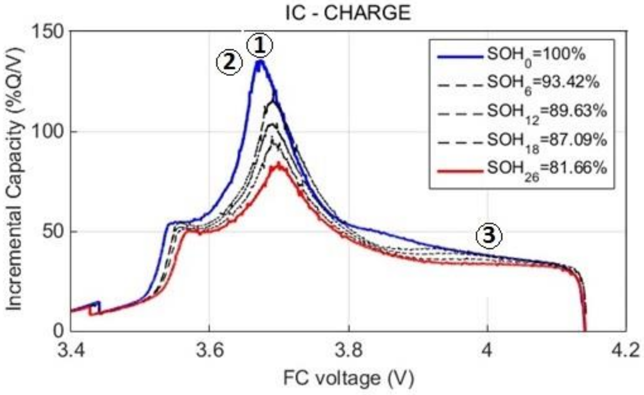

Figure 3: IC obtained at charging from BoL until and 81.66% SoH at 80% DoD.

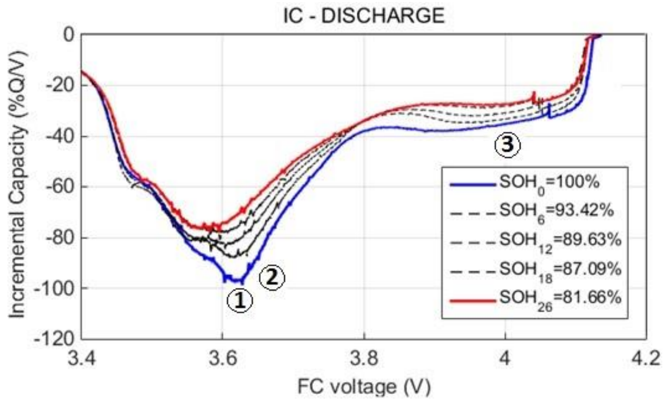

Figure 4: IC obtained at discharging from BoL until and 81.66% SoH at 80% DoD.

3.3 Verification

The verification consisted on testing the mentioned 3 cells at different SoHs. In total, more than 75 different scenarios were measured in order to test the algorithm.

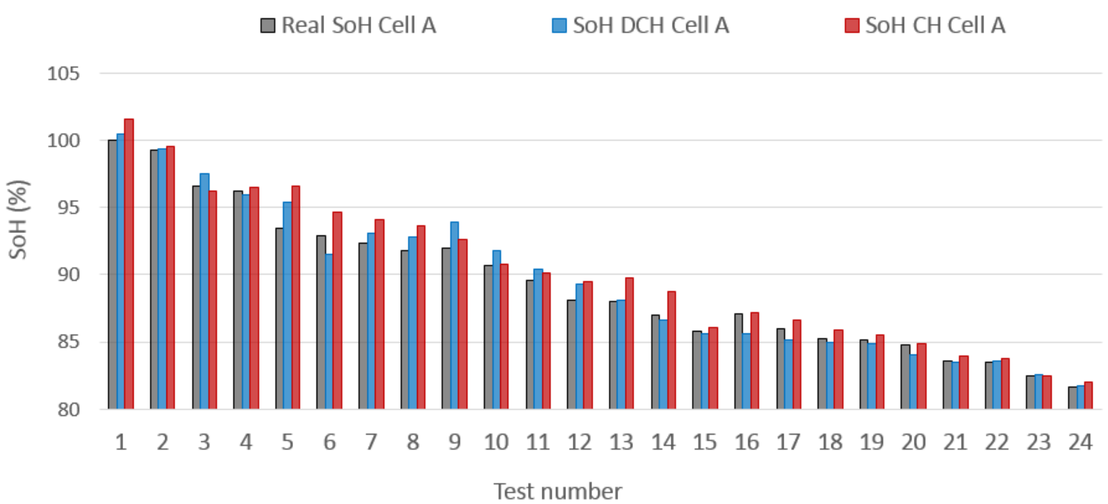

Figure 5: Real measured SoH in grey, estimated SoH through discharge in blue and the estimated SoH through charge in red, all for cell A tested at 80 % DoD.

Cell A, was cycled at 80 % DoD, reaching the EoL state coming up to 80 % SoH. Figure 5 shows the obtained result from both developed algorithms. In grey the measured real SoH is shown obtained from the developed capacity test at each moment. In blue the estimation obtained from the discharging algorithm is presented and in red the estimated result when charging.

Figure 6 shows the differences between the real SoH measurements and the results obtained through discharging in blue, and in red the difference compared this time with the estimation when charging the cells. Even though the average results represented in figure 6 do not differ much between charging (0.84 %) or discharging (0.67 %), the obtained maximum difference from both cases do present an obvious difference. For charging the maximum difference corresponds to 3.14 % and in discharging is much lower, 1.98 %.

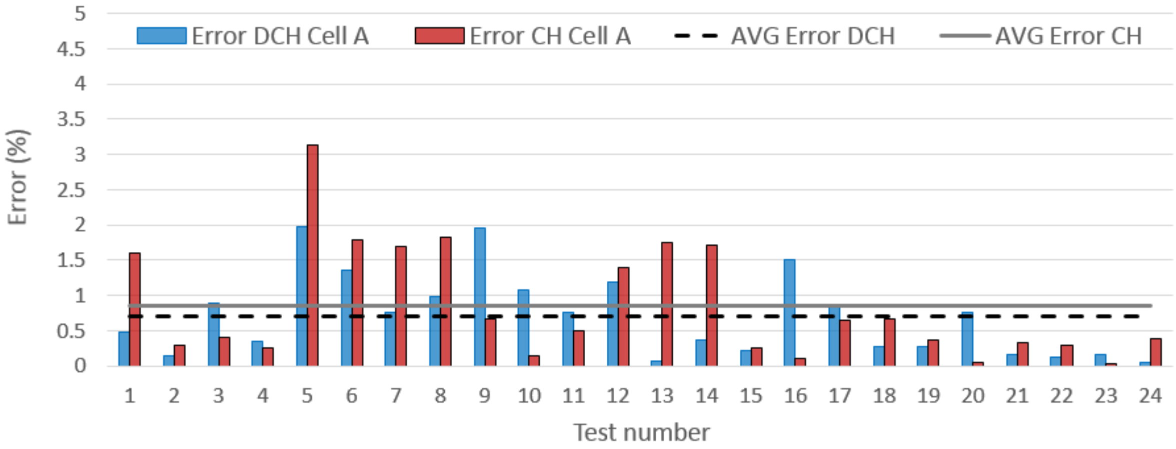

Figure 6: Obtained difference between the real SoH and the estimated SoH through discharge in blue and through charge in red. Average of the obtained difference, for discharge in dashed black, for charge in full grey.

Cell B, was cycled at 60 % DoD, reaching only a 95 % SoH. Figure 7 shows, in the same way as before, the obtained result from both developed algorithms compared to the real measured SoH. Regarding the results obtained for this cell (figure 8), the maximum and average differences at both cases differ quite a lot from each other. At charging the maximum difference corresponds to 2.99 %, and at discharging 1.21%. According to the average results, for charging is 1.49 % and when discharging 0.65%.

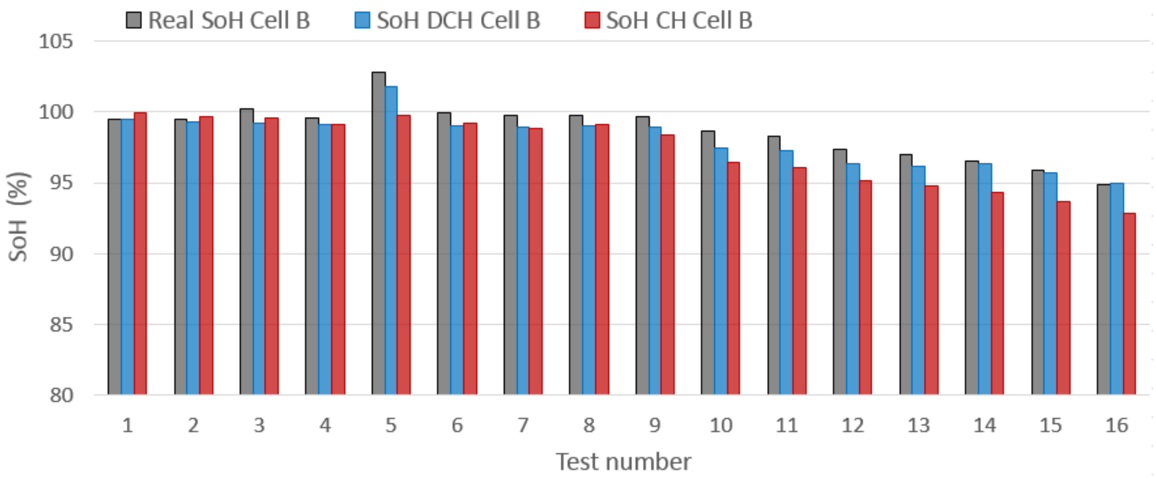

Figure 7: Real measured SoH in grey, estimated SoH through discharge in blue and the estimated SoH through charge in red, all for cell B tested at 60 % DoD.

Finally cell C, was cycled at 30 % DoD, reaching a 90 % SoH. Obtained results (figures 9 and 10) show that both the maximum and average results in both testing cases are very similar. The charging maximum difference is 1.36 %, and at discharging 1.24 %. The average results, for charging is 0.55 % and when discharging is 0.49 %. The average results differs in less than 0.06 % and the maximum differences differ in less than 0.12 %. From all the 79 tested scenarios of the 3 cells, it can be highlighted that the more tests, the better results are obtained.

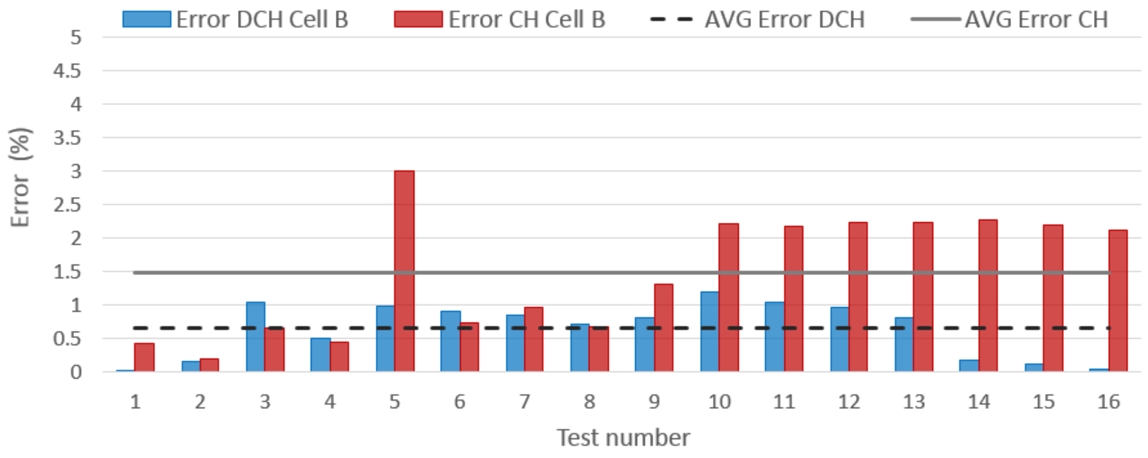

Figure 8: Obtained difference between the real SoH and the estimated SoH trough discharge in blue and through charge in red. Average of the obtained difference, for discharge in dashed black, for charge in full grey.

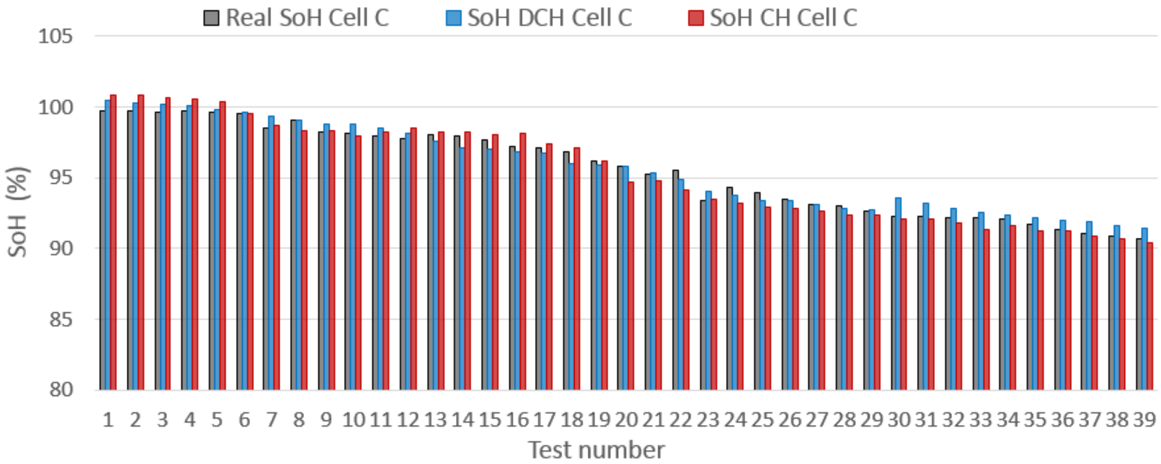

Figure 9: Real measured SoH in grey, estimated SoH through discharge in blue and the estimated SoH through charge in red, all for cell C tested at 30 % DoD.

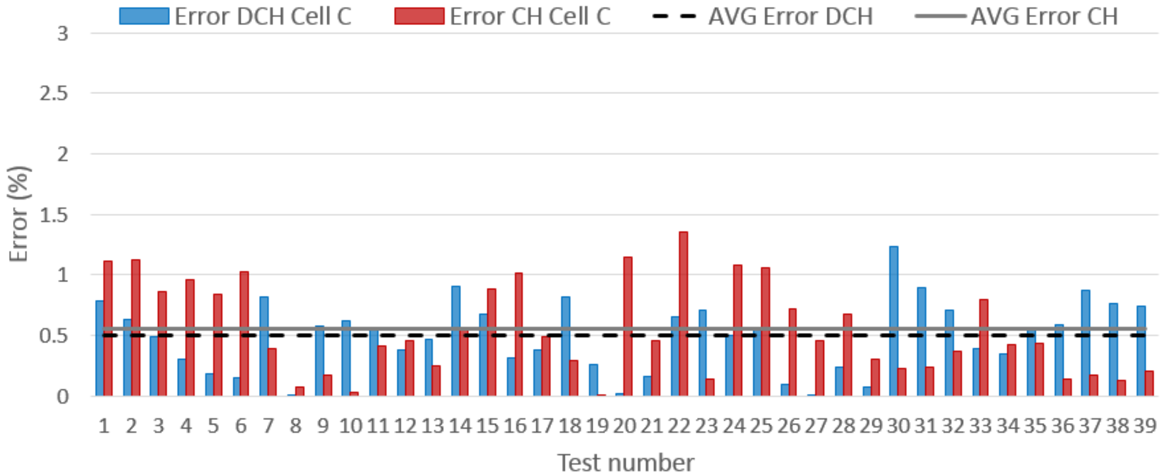

Figure 10: Obtained difference between the real SoH and the estimated SoH through discharge in blue and through charge in red. Average of the obtained difference, for discharge in dashed black, for charge in full grey.

Table 3 shows the maximum and average errors of all tested curves, at both ways charging and discharging. From it, it can be highlighted that the discharging algorithm shows better results than the ones obtained through charging performances.

Table 3: Maximum and average results obtained from the charging and discharging tests.

	Discharge		Charge	
	Max. %	Avg. %	Max. %	Avg. %
Cell A	1.98	0.69	3.13	0.84
Cell B	1.23	0.49	1.36	0.55
Cell C	1.2	0.64	2.99	1.49

4 Validation

The algorithm has been also validated at module level. Each module contains 14 cells, which are tested at the same time through the same charge or discharge. The developed algorithm consists on an online partial charge or discharge. As the complete charge or discharge is not needed, the method is considered partial. Accordingly, the required time will be shorter compared to a whole charge or discharge.

The procedure is applied individually to each cell. This comes from a valuable reason: the detection of early degraded cells inside a battery pack can accelerate the degradation of all cells and create risky failures at premature states. In order to detect individual SoH of each cell, the algorithm is performed in every single cell. Therefore, the algorithm has been implemented in the next battery pack prototype (figure 11) developed entirely by IKERLAN. The programming of the algorithm has been made in a LabView environment supported by a National Instrument microcontroller.

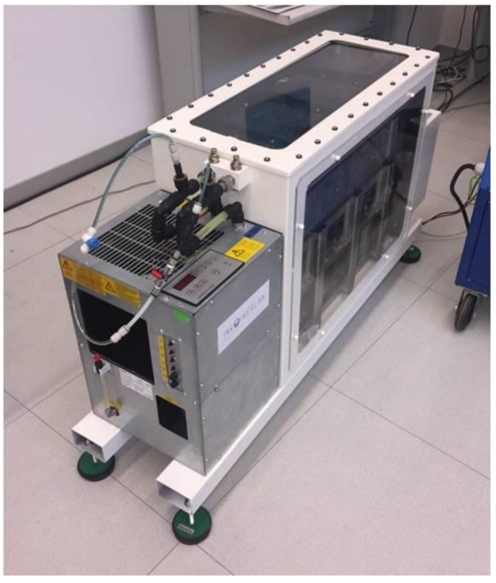

Figure 11: Developed prototype.

Apart from the fact of saving time, the feature of running the algorithm through partial charges or discharges gives a highly valuable advantage: cell voltage will never reach high and low limits which are considered risky for the battery. On top of this, in case the application needs the use of the battery while the estimation is running the algorithm can be stopped at any time and the energy storage system will always be able to provide energy.

The algorithm has been tested in new modules which are in good condition. The SoH result therefore, should correspond to an approximate value of 100% for all cells. The obtained SoH results from the algorithm applied to one of the tested modules, are presented in figure 12 for both cases, charging or discharging. Blue bars show the discharging results and red bars represent the charging outcomes. In addition, for an easier reference it will be considered 100% as the ideal value for all cells. This constant value is represented as a dashed dark line. The presented results have been obtained from three charging and discharging tests made consecutively, from the three results the average was obtained and showed as a result next.

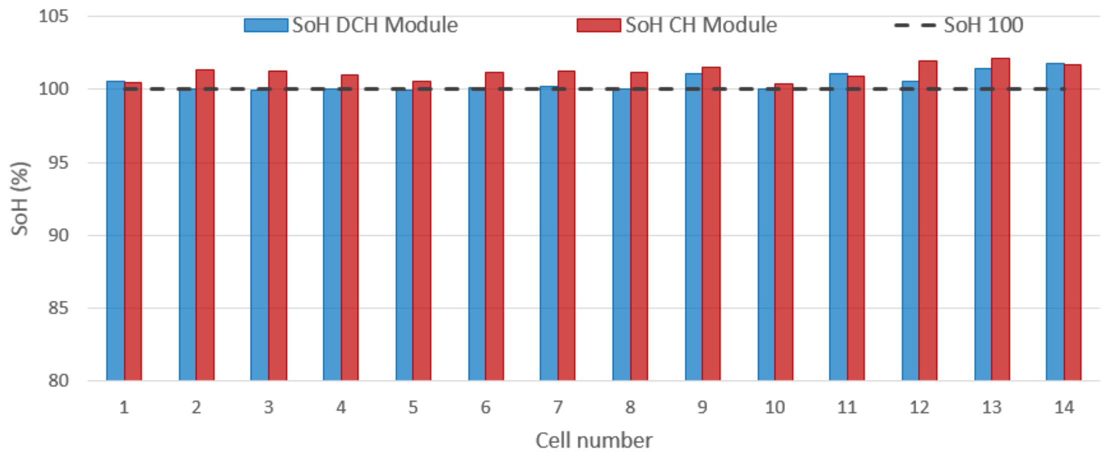

Figure 12: Original results of the tested module, red bars show the algorithm response when charging, blue ones when discharging.

In figure 13 the comparison of the obtained errors is shown. The errors have been calculated taking as the correct value 100% SoH, which doesn't necessarily has to be that exact value. In any case it will be used as a guidance. The collected results express that the maximum error at discharging corresponds to a 1.78%. The average error of all 14 cells when discharging is reduced to just 0.509%. For the charging procedure, both values, maximum and average increase a bit comparing to the discharging results. The maximum difference between the ideal and the estimated result is around 2% but the average is reduced up to 1.19%. As a conclusion, these results show that the discharging algorithm gives more accurate results.

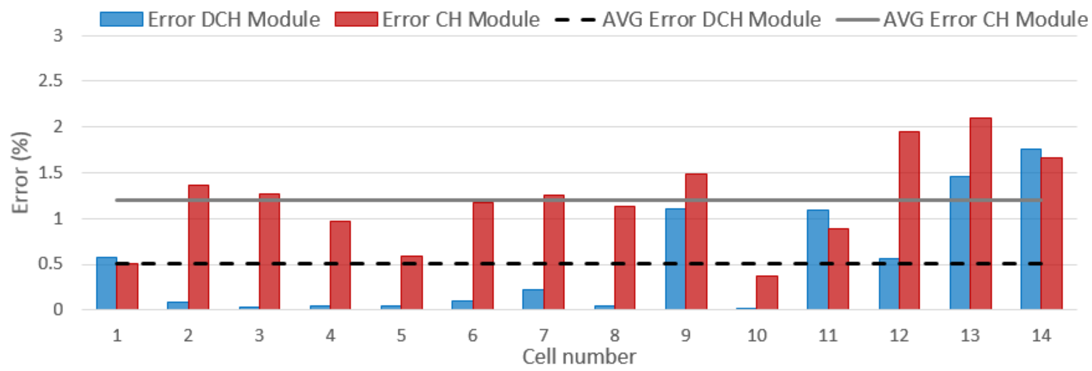

Figure 13: The difference of the results of the tested module, red bars show the algorithm response when charging, blue ones when discharging.

5 Conclusions

The developed algorithm is based on the detection and measurement of three features of interest obtained from two key points at the charging or discharging IC curves. The algorithm has been implemented in a microcontroller through its programming in LabView. Through the same charge or discharge test, all 14 cells are tested and the SoH for each cell is calculated. It is indeed a light procedure so it can be implemented easily in a real microcontroller without the need of extra computing power. Moreover, the estimation is purely on-line meanwhile the test is running, so there is no added time which will delay the result extraction.

Using partial charges or discharges for SoH estimation is highly recommended due to the benefits it brings. First, the fact that no high or low voltage limits are reached makes the use of the cell and consequently of the battery pack safer. Secondly, when a complete discharge is not necessary to be reached, brings the opportunity of giving always priority to the application usage. In other words, if the algorithm process is running but the application is needed, the application will always have energy in order to cover it needs. Moreover, both ways, charging and discharging procedures showed high accurate results, estimating the SoH within an error less than 2%. This gives complete freedom to choose the process that fits better the application usage.

All these characteristics makes the algorithm suitable for its online implementation in a real application. In addition, it contributes to a better and more efficient use of the energy of the battery pack, giving always priority to the application usage. Furthermore, the obtained results show that the developed algorithm is highly accurate and precise.

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