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Dedicated to the memory of Academician Gleb Drăgan

COMPARATIVE STUDY OF SCREENING METHODS FOR SECOND LIFE $LIFEPO_4$ BATTERIES

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Once the first generation of electric vehicles will reach the end of life for their batteries, local governments and battery producer will be facing a real problem. These batteries while they do not meet the requirements for the automotive industry any more, still have around 80 % of their initial capacity which makes them reusable in other applications. In order to do so, they have to be properly evaluated so batteries with similar characteristics are used in new battery packs. This paper analyzes three of the most common screening methods in terms of accuracy, complexity and operational time. This is done by developing a multi-criteria analysis, which scores each method.

1. INTRODUCTION

In the last period, a substantial growth in the number of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) was observed sustained by a growing concern of pollution-related issues and health problems. The batteries that equip this first generation of EVs and PEHVs reached their end-of-life (EoL) limit and will begin to be replaced [1].

The fate of these batteries is regulated in EU by Directive 2000/53/EC – A review of dynamic material flow analysis methods and Directive 2006/66/EC – Batteries and Accumulators and Waste Batteries and Accumulators which mandate battery manufactures and local governments to properly collect and recycle batteries when they are no longer in service [2,3]. Recycling of the batteries can produce secondary raw materials that can be used to produce new batteries increasing the degree of circularity and limiting the extraction of new materials. On the other hand, these so-called 'retired' batteries still have around 80 % of their initial capacities, but they are put out of service because they do not meet the safety regulation of automotive industry and transportation laws. These aspects lead to the concept of giving a second life to electric vehicle batteries and reusing them in other applications with lower current rates and energy storage demands such as uninterrupted power supplies (UPS), small home appliances, buffers, personal transportation devices, etc. [2,4].

These applications will help to prolong the usage life of batteries and also reduce their cost for the lifetime, which, in return, will help to the popularization and generalization of EVs [1].

Although the economic benefits of the retired batteries are attractive, from the literature survey done [2,5–11], they cannot be reintegrated in other applications as-is. Several factors related to aging mechanism make necessary preliminary screening processes in order to determine batteries with suitable characteristics. Otherwise, batteries with poor consistency can easily be overcharged or over-discharged, which can lead to heat runaway, risk of explosion, etc. [9,12,13].

Traditionally screening approaches for automotive batteries include:

- A full charge-discharge test. This method is very accurate and reliable, but it is time-consuming and costly and cannot be applied to large-scale battery screening [5,14].
- Open circuit voltage (OCV) measurements. It is based on applying different current pulse and measuring the relaxation time of batteries. While faster than the full charge-discharge test, it is still not suitable for large scale screenings [6,10].
- Internal resistance methods, based on dc pulse charge/discharge or ac analysis. These methods involve quick tests, but the end result is obtained only after extensive data processing [15,16].
- Statistical approaches which investigate the capacity and impedance distribution of cells within a battery pack. These approaches require extended data from when the battery was in use [17].
- Machine learning methods. Typically, these are represented by predictive filters [18], genetic algorithms, support vector machines and artificial neural networks [9] which are based on a large set of data for training and usually produce high efficiency.
- Hybrid methods that are obtained by combining one or several above mentioned techniques in order to obtain a quick and accurate screening process [19].

All these methods are done at the cell level, but they can be used for module screening as well.

In this study, are analyzed some of the most common methods in terms of accuracy, complexity and operational time. For this, a multi-criteria analysis (MCA) is developed to calculate a score for each method. The study is performed on three LiFePO4 (LFP) batteries that were randomly chosen from a battery lot whose parameters were previously determined.

The main contributions of the paper include the following aspects:

- A detailed analysis of the most common screening methods (Section 2).
- The development of the multi-criteria analysis (Section 3) for scoring each method.
- An experimental study for determining the best-suited method for chosen LFP batteries (Section 4).

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2. SCREENING METHODS

All screening approaches are two-stage processes. In the first step, all the batteries are visually examined in order to remove all those that present corrosions, swellings, actuated valves, or any other sign of defect. Only the batteries that pass the first test can be used in second-life applications and are submitted to the sorting methods.

The previously presented approaches fall in one of two categories, either they are based on quick tests with relatively low accuracy, or they require historical data from when the battery was, in order to improve the results.

Considering the growing number of retired batteries that will appear in a short period, we feel that the optics of screening methods should change and the focus will be on developing very rapid methods. Regarding the accuracy of the methods, this should be around 3 %. This value is the initial battery capacity inconsistency from any battery pack with BMS [20].

In this context, the efficiency of the internal resistance methods will be analyzed. These methods are the fastest reported to the accuracy of the full charge-discharge test, which is the most accurate.

2.1. INTERNAL RESISTANCE METHODS

The internal resistance methods are divided by the type of power used in dc methods and ac methods. The dc methods require a charge or discharge pulse followed by the Ohm's law to calculate the internal resistance under sufficient rest conditions (1).

$$R_{\Delta t} = \frac{U(t+\Delta t) - U(t)}{I}, \quad (1)$$

where $U(t)$ and $U(t+\Delta t)$ are the voltages at the beginning and at the end of the pulse and I is the value of the current pulse applied.

The value of the current pulse is usually equal to the nominal capacity of the battery (1 C), and the period for it is between 2 and 30 s. In this study, an 18 s pulse will be used, in concordance with the hybrid pulse power characterization test (HPPCT) from the partnership for new generation of vehicles (PNGV) manual [21].

The ac methods use a 1 kHz signal or higher to excites the battery and then the Ohm's law calculates the resistance. The ac method usually shows different values than the dc method but both readings are correct [22]. In order to determine the age of the battery through resistance methods, the evolution of the resistance according to the number of discharge cycles should be previously known.

2.2. FULL CHARGE-DISCHARGE APPROACH

In this case, the battery is fully charged using a constant current – constant voltage (cc-cv) device in respect with the maximum voltage provided by the manufacturer and after a rest period that is usually 1 hour, the battery is discharged (at the nominal current) until the cut off voltage is reached. The age of the battery is determined by calculating the state of health (SoH) – 2 of the battery and then applying the same percentage to the number of discharge cycles provided by the manufacturer

$$\text{SoH} = \frac{Q_D}{Q_n} \cdot 100, \quad (2)$$

where Q_D is the discharged capacity and Q_n is the nominal capacity.

3. MULTI-CRITERIA ANALYSIS

MCA is a tool for comparison and ranking of the different results, especially when a single criterion is not enough. It deals with several concepts like criteria, options, performance matrix, score and weight [23].

The options are items that are subject to comparison. After the MCA is performed, the best one is selected in conformity with the chosen criteria. In our case, the options are the three selected screening methods: dc resistance, ac resistance and the full charge-discharge cycle.

A criterion is a scale according to which the options are evaluated. Each criterion evaluates a relevant aspect of the option and is independent of the others. For this study, the criteria are the complexity of the methods, the accuracy and, most importantly, the operational time.

The weights represent a percentage value assigned to each criterion to highlight its importance. In our case, due to the fact that we want to obtain an objective as possible screening method, all the weights are equal to 33.33 %.

The concepts presented earlier are systematically represented as the performance matrix of the MCA. Here each row represents an option and each column includes an evaluation criterion. The values that are recorded in each cell represent the performance level of an option for a particular evaluation criterion.

4. RESULTS AND DISCUSSIONS

For accurately evaluating the three screening methods, we randomly have chosen three LFP batteries from a 20 batteries lot. The characteristics for all the batteries were determined over a two-year period and each parameter for a corresponding state of charge (SoC) was recorded. To simplify the process, the temperature was constant during all the tests and for this study is still constant. The nominal characteristics of a battery are presented in Table 1.

Table 1

LFP Battery Characteristics

Characteristic	***Value***
Nominal capacity [mAh]	1450
Cut-off voltage [V]	2.50
Maximum charge voltage [V]	3.65
Nominal discharge current [A]	0.7
Maximum continuous discharge current [A]	2.1
Internal resistance [mΩ]	< 40
Number of cycles to DoD 80 %	1000

To characterize the lot, the battery with the most average behavior and was chosen and its evolution of the dc and ac resistances is presented in Fig. 1. This evolution was also estimated through curve fitting techniques and hence equation (3) and (4) were obtained.

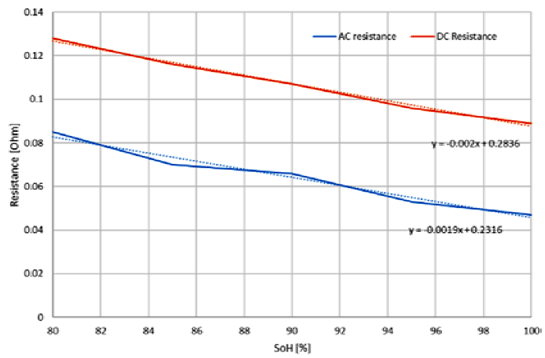

Fig. 1 — The evolution of resistance over SoH.

$$R_{AC} = -0.0019 \cdot \mathrm{SoH} + 0.2316 \quad (3)$$

$$R_{DC} = -0.002 \cdot \mathrm{SoH} + 0.2836\,. \quad (4)$$

In order to determine the parameters needed for the MCA, three LFP batteries were submitted to an extended experimental study. First, the batteries were charged using a CC-CV method and then after a rest period of 1 hour they were discharge with a 0.7 A current. The discharged capacities were measured and the time needed to do so was recorded as the operational time for this approach. After another rest period, the batteries were fully charged left them to rest for 1 hour again. The ac resistance was measured using a commercially available ACR 1 kHz battery tester. In the end, a 2.1 A discharge pulse was applied for 18 seconds and the starting and ending values of the output voltages were recorded. The obtained results are presented in Table 2.

Table 2

LFP Battery results

Battery number	Screening methods		
	Full charge-discharge [mAh]	R_{dc} [Ω]	R_{ac} [Ω]
1	1194	0.116	0.065
2	1191	0.118	0.063
3	1151	0.124	0.084

Using (3), (4) and the values from Table 1, the age of each battery as the number of discharge cycles was determined – Table 3.

Table 3

Age of each battery

Battery number	Age according to each method		
	Full charge-discharge	R_{dc} [Ω]	R_{ac} [Ω]
1	823	838	876
2	821	828	887
3	793	798	776

The actual age of each battery is 850 cycles for batteries 1 and 2 and 800 cycles for battery 3.

To evaluate the complexity of each method, the number of steps needed to reach the value of the batteries' age was considered. In this case, the full charge-discharge cycle is the least complex and gets value of 1, the R_{ac} method requires two steps – value of 2 and R_{dc} test because of the fact it needs an extra step given by applying (1), it receives the value of 3.

The obtained results consist the basis for scoring each criterion necessary in the MCA – Table 4.

Table 4

Values for the MCA criteria

	Criteria			
	Battery	Accuracy	Complexity	Operation time
Full C-D	1	96.82 %	1	6521 s
	2	96.58 %	1	6483 s
	3	99.12 %	1	5944 s
R_{dc}	1	98.58 %	3	18 s
	2	97.41 %	3	18 s
	3	99.75 %	3	18 s
R_{ac}	1	96.94 %	2	1 s
	2	95.64 %	2	1 s
	3	97.00 %	2	1 s

In order to develop the MCA performance matrix – Table 5, the best values were awarded with 100 points and for the others, a proportional score was used. Also, each score was multiplied with its appropriate weight.

Table 5

MCA performance matrix

	Criteria				**Total**
	Bat	***Accuracy***	***Complexity***	***Operation time***	
Full C-D	1	32.03	33.33	0.01	**65.37**
	2	31.95	33.33	0.01	**65.29**
	3	32.79	33.33	0.01	**66.13**
R_{dc}	1	32.61	11.11	1.85	**45.57**
	2	32.23	11.11	1.85	**45.19**
	3	33	11.11	1.85	**45.96**
R_{ac}	1	32.07	16.5	33.33	**81.90**
	2	31.58	16.5	33.33	**81.41**
	3	32.09	16.5	33.33	**81.92**

As can be seen from the values of Table 5, even though the R_{ac} method has the smallest values for the accuracy, it compensates in terms of complexity and operational time and scores an average of 81.74 points, which makes it the best method for the chosen criteria. Its low accuracy compared to the other methods, is only in a 2 % interval, and some part of it is related to eq. (3) which does not fit the experimental data as good as the other equation.

On the other hand, the R_{dc} method has the best accuracy, but this comes from a high complexity process which is also time consuming which makes this method to score only 45.57 points. The full charge-discharge test was chosen here for reference purposes only and manages to score an average of 65.59 points.

5. CONCLUSIONS

In this paper, three of the most common screening methods for LFP batteries were analyzed in terms of accuracy, complexity and operational time. For this, a balanced MCA was developed and used to determine a score for each method according to the chosen criteria.

The score of the internal resistance method using ac power was the highest with 81.74 points. The main advantage of this method is that it can be performed very fast in only 1 s and although it has the lowest accuracy, this in only in a 2 % limit. Overall this method offers the best compromise between operation time, accuracy and complexity which makes it ideal for screening large number of LFP second life batteries.

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