Mathematical modeling of aging factors for Li-ion battery cells

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Abstract- **Battery's aging could be characterized using four crucial parameters defined as the 'aging factors', which are: residual capacity, internal resistance, peak power and Open Circuit Voltage. A 'black box' modeling approach is used to estimate them in function of time and usage conditions. The model is based on regression linear or non-linear techniques applied to experimental data. The Multiple Linear Regression (RLM) method is proved to be efficient for the only OCV model, while Support Vector Machine (SVM) gives satisfying results for the four aging factors.**

***Keywords*: Linear and non-linear Regression, Modeling, Battery cells aging, Lithium-ion**

INTRODUCTION

Battery aging assessment is essential for the optimal management of a fleet of electric vehicles. It depends on the battery technology, usage conditions, storage conditions and recharge strategy. Among the rechargeable battery systems available at present, the Li/Li-ion systems provide the highest energy densities [1] [6] [7]. This makes them the most attractive candidates for electric vehicles. Meanwhile, new technologies of Li/Li-ion keep appearing till our days, with different chemical compositions. This can create new electrochemical phenomena influent on aging, that need to be modeled. To prevent this problem, mathematical models using 'black box' approach could be used. The outputs of the model are estimated in function of selected inputs without the need of studying all of the electrochemical phenomena inside the battery cell.

Battery aging can be characterized with many parameters but four crucial parameters can be defined as the 'aging factors': residual capacity, internal resistance, peak power and open circuit voltage (OCV). The aging model will be divided in two complementary steps. The first one is the modeling of the four aging factors as depicted in Fig. 1, This block will be used in the second step to estimate the aging as shown in Fig. 2.

In the present paper, only the first step of modeling will be presented (Fig. 1). It allows estimating the value of each of the four 'aging factors' in function of the cell usage and storage conditions. It is based on a mathematical model built from experimental data. The experimental procedures, the mathematical methods used in the study and the simulation results are detailed in this document.

Fig. 1. Aging factors model block. *Peak Power and ΔSOC are used only in cycling tests. **Storage SOC is used only in storage tests.

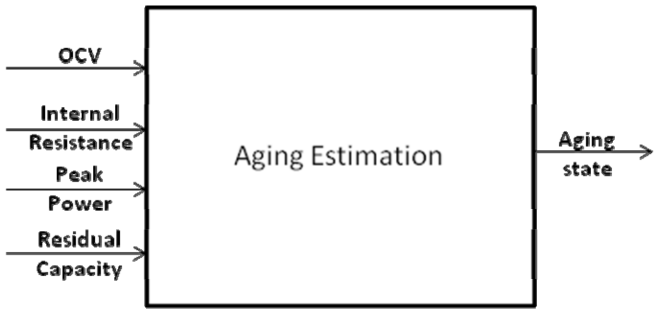

Fig. 2. Aging estimation block

EXPERIMENTAL

The experimental data are coming from tests made in an European program [2]. They are extracted from check-up tests, which were periodically made each 6 weeks. There was two types of test procedures (cycling and storage) to

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characterize the two aspects of aging. The experiments were performed for two types of Li/Li-ion battery cells (Energy and Power cells).

A. *Cycling test procedures*

Micro-cycles are repetitively applied on battery cells "Fig. 3". The discharge rate depends of the current rate, SOC width (ΔSOC) and the cycle type (Energy or Power). In the case of Energy cells, the cell is discharged at the end of each micro-cycle, until 80% of depth of discharge (DOD) is reached. A recharge procedure is then applied to fully recharge the cells. While in the case of power cells, discharge rate is equal to zero, and the micro-cycles are applied without stop. Three parameters vary in these procedures: the current rate, the SOC width and the cycling temperature.

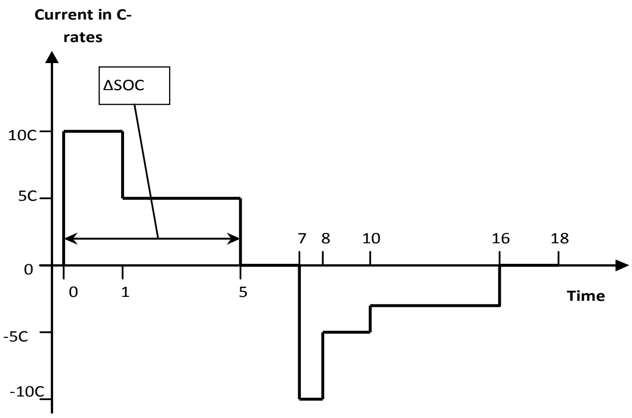

Fig. 3. A micro-cycle for power cells

B. *Storage test procedures*

In storage procedures, battery cells are stored at different temperatures and SOC values.

C. *Test Conditions*

Both cycling and storage tests are performed in different conditions. This allows to evaluate the influence of cycling and storage parameters on the aging process. There are two types of cells used in the tests: 45 Ah high-energy cells and 30 Ah high-power cells. As mentioned before, the temperature and the storage SOC are the two changing parameters in the storage procedures, while current rate, temperature, SOC and ΔSOC are the parameters that change in the cycling procedures. Tables 1, 2 and 3 resume the test conditions of the experimental tests.

T \ SOC	30%	50%	70%	90%	100%
35°c					√
45°c			√		√
60°c	√	√	√	√	√

TABLE I. Storage Conditions matrix (SOC vs. temperatures values)

T \ Cycle	30%	50%	70%	90%
0°c	√	√		
40°c	√	√	√	
47°c		√	√	√
60°c			√	

TABLE II. Cycling conditions matrix (cycle types vs. temperatures values)

Current rates (Cr) and ΔSOC values used in cycling tests depend of used microcycle as follow:

P1 (High-Power): Cr = 10 C / ΔSOC = 10%

P2 (High-Power): Cr = 5 C / ΔSOC = 10%

E1 (High-Energy): Cr = 2 C / ΔSOC = 2%

E2 (High Energy): Cr = 1 C / ΔSOC = 1%

Where C is the rated capacity (Ah) of the cell.

MODELING

The chosen modeling method is a 'black box' using regression technique that allows estimating the four aging factors in function of time, and five usage and storage conditions, which are: temperature, SOC, peak current, SOC width and storage SOC. The study was conducted in two different cases according to the chosen regression technique: either linear or non-linear. In both cases, two data sets were used:

- Learning set, containing 70% of data, randomly chosen.
- Testing set, containing the30% rest of data. The aim of this data set is to validate the model for a new set of data.

A. *Multiple Linear Regression (MLR)*

The Multiple Linear Regression (MLR) [2] method was first used. It consists on estimating the output variables of the model '$\hat{y}$' (aging factors) supposing the existence of a linear relation with the inputs 'x':

$$\hat{y}_j = a_1 \cdot x_{j1} + a_2 \cdot x_{j2} + \cdots + a_n \cdot x_{jn} + b \qquad (1)$$

$$\varepsilon = \hat{y} - y. \qquad (2)$$

ε is the estimation error and y is the measured value.

The coefficients a_i are calculated in a way to minimize the quadratic error ε^2 [3]. The solution is:

$$A = (X'X)^{-1}X'Y \qquad (3)$$

ε is the estimation error and y is the measured value.

The coefficients a_i are calculated in a way to minimize the quadratic error ε^2. The solution is:

B. Support Vector Machines (SVM)

As it will be showed later in this document, MLR technique was insufficient to model all the 4 of 'aging factors'. Therefore, the use of a non-linear technique was necessary. The SVM method was chosen because of its universal approximation property [4].

$$\hat{y}_j = \sum_{i=\&}^{N} \alpha_i k(x, x_i) + b \tag{4}$$

K(x,xi) is called the kernel function, it is chosen to be the RBF Gaussian function in our study:

$$k(x, x_i) = e^{-\frac{\|x - x'\|^2}{2\sigma^2}} \tag{5}$$

The problem could be reduced to minimizing [5]:

$$\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(\mathbf{x}_i, \mathbf{x}_j) + \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)y_i \tag{6}$$

With the following constraints:

$$\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \tag{7}$$

$$0 \le \alpha_i^{(*)} \le C,\ i \in \{1, \ldots, n\} \tag{8}$$

RESULTS

A. Multiple Linear Regression (MLR)

This method has showed good results with the OCV model (Determination coefficient $R^2 > 0.9$ and a relative error < 1%) (Fig. 4), and was inefficient in the other three cases (Relative error > 20% in most of the cases) (Fig. 5).

Figures below (4 to 8) illustrate the estimated values (y axis) in function of the real values (x axis). In order to have a good estimation, the graph must be similar to the line of function: y = f(x) = x. Black points correspond to learning set, red ones to testing set.

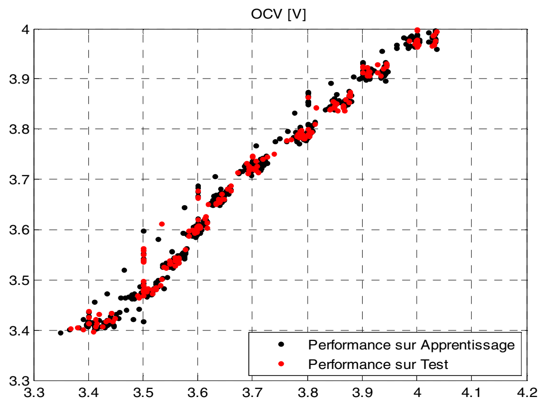

Fig. 4. Estimated OCV values using MLR in function of measured ones. The graph is similar to the line: y = x.

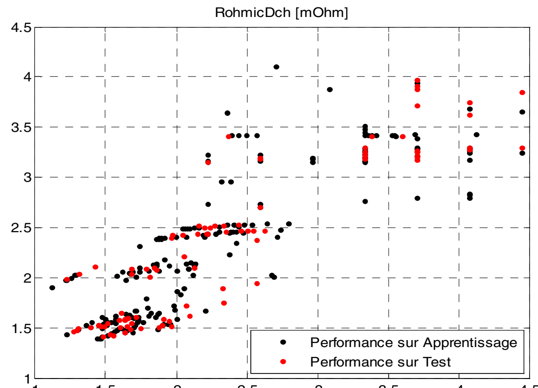

Fig. 5. Estimated Internal resistance values using MLR in function of measured ones.

B. Support Vector Machines (SVM)

The modeling results were satisfying for the four aging factors. The determination coefficient was always superior to 0.95 and the relative error inferior to 5%.

The figures below (6, 7 and 8) show some samples of the results. The graphs illustrating the estimated values in function of the real ones are always similar to the line: y = x.

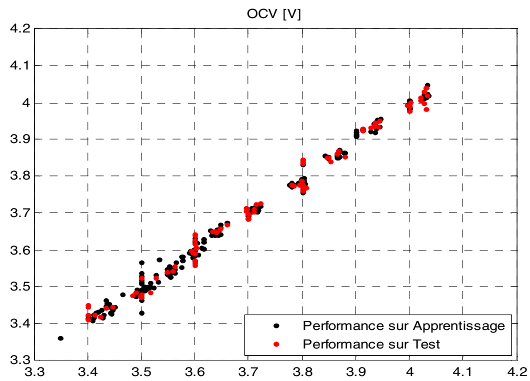

Fig. 6. Estimated OCV values using SVM in function of measured ones

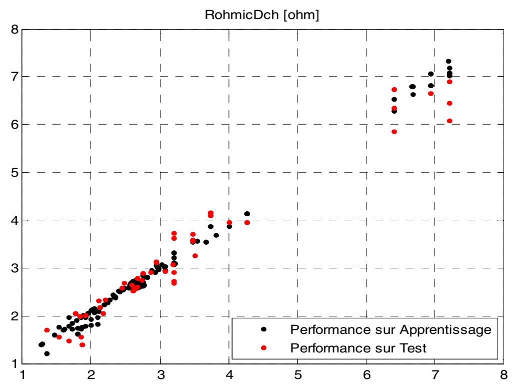

Fig. 7. Estimated Internal resistance values using SVM in function of measured ones.

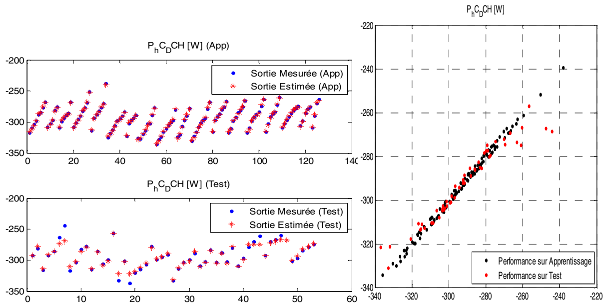

Fig. 8. . Estimated peak power values using SVM (red) and measured values (blue) on the same graph on the left (learning and testing sets). Estimated peak power values using SVM in function of measured ones.

CONCLUSION

A mathematical black box approach was presented in this document for modeling crucial aging parameters called ‘aging factors’. The method is based on regression techniques. Two types of regression techniques were used. The MLR was satisfying only with OCV modeling, while SVM method proved to be able of modeling all of the four ‘aging factors’.

These facts mean that the chosen inputs are sufficient to estimate the four aging factors using regression techniques, at least if they respected the same conditions of the test procedures. Other conclusion could be made, which is that the relationship between OCV and the chosen inputs is proved to be linear, and is non-linear for the three others aging factors (residual capacity, internal resistance and peak power).

There still other aspects to be treated to improve the study:

- Other potential important inputs, as recharging strategy should be taken in consideration in the study to make the model more general.
- The second part of the model (Fig. 2) still has to be developed. It consists on estimating the aging state in function of the ‘aging factors’.

The method presented above will be used as a part of a global model of an electrical car, predicting its behavior in function of time and usage conditions.

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