Characterizing the Degradation Process of Lithium-ion Batteries Using a Similarity-Based-Modeling Approach

Aramis Perez[1], Francisco Jaramillo[2], Vanessa Quintero[3,4], and Marcos Orchard[5]

[1,2,3,5] *Department of Electrical Engineering, University of Chile, Av. Tupper 2007, Santiago, Chile*
aramis.perez@ing.uchile.cl
francisco.jaramillo@ing.uchile.cl
vquintero@ing.uchile.cl
morchard@ing.uchile.cl
[4] *Faculty of Electrical Engineering, Universidad Tecnológica de Panamá, Av. Centenario, Panamá, Panamá*

Abstract

This article proposes a Similarity-Based-Modeling (SBM) approach capable of characterizing the degradation process of a lithium-ion (Li-ion) battery when discharged under different current rates and different State-of-Charge (SOC) ranges. The degradation process can be represented through a biexponential model. Understanding the degradation process is a matter of utmost importance since the after each time the battery is used, the availability to store and deliver energy decreases. Even though manufacturers provide important information that explains the degradation process of the Li-ion batteries when used always under the same conditions, this information many times is not enough due to the different ways a single battery can be used through its lifespan. This behavior creates the necessity to use the available information and extrapolation techniques to model the degradation process when variable operating conditions are present in each cycle. This will allow the user to understand when the Li-ion battery will complete its lifespan with a known uncertainty, aiding a possible decision-making task. In this regard, it is possible to determine the equivalent cycle-by-cycle efficiency which has low values at the beginning of the degradation process until it reaches a higher and steady value. The lifespan of the batteries is analyzed through the use of Monte Carlo simulations which intends to represent a more realistic way of how the batteries are used.

1. Introduction

The popularity of Li-ion rechargeable batteries is increasing day by day due to all the applications in which they are used. Some of the possibilities are: cell phones, tablets, notebooks, small electronics, satellites, wireless sensor networks, or even electromobility solutions such as electric bicycles electric cars (Olivares, Munoz, Orchard, & Silva, 2013). Regardless of the application in which Li-ion batteries are used, two major concerns require full attention by the user. The first of the concerns has to do with the short term performance of the battery. In this sense, an indicator known as the SOC is useful since it quantifies the amount of energy available in the battery prior to reaching the discharge threshold (Hannan, Lipu, Hussain, Saad, & Ayob, 2018). The other concern is related to the long time performance of the battery and how much lifespan it has before reaching is End-of-Life (EOL). The indicator used to quantify the degradation process is the State-of-Health (SOH) (Guha & Patra, 2018). Usually manufacturers inform the users through datasheets about how much lifecycles they can expect from a battery under certain operating conditions. However the information provided is not enough to understand the degradation process if the operating conditions are changed. For example, typically the datasheets illustrate the degradation process of the batteries when discharged at nominal current, under constant ambient temperature, and completing fully discharge cycles. This means that each cycle is defined as going from a fully-charged state to a fully-discharged state (without over charging or over discharging the battery). Although this information is useful, it might not be enough to characterize the degradation process of the batteries since the use might not always be the same (Perez et al., 2017). Even more, (Yang, Wang, Xing, & Tsui, 2017) states that the degradation process of Li-ion batteries can follow two types to trends, convex or concave depending on the chemistry of the Li-ion battery. A clear example of how the operating conditions are not uniform, is the use of cell phones or tablets since most users charge the battery while resting, and the next charge period might start before the SOC reaches a 0%. One of the reasons for doing this, is that most users desire to have as much energy available for those times in which charging the batteries is not possible.

Another example are electric cars since the majority of e-car owners don't wait until the battery is discharged for recharging it. Even though there are no references for this behavior, it is something that can be justified by observing the typical usage patterns of the users. For this reason, it is important to find a method that characterizes the degradation process of Li-ion batteries when the operating conditions are different as the ones from reported by the manufacturer. This article proposes a methodology that characterizes the degradation process of Li-ion batteries using a SBM approach when discharged at different current rates regardless of the SOC at which they are used.

2. THEORETICAL BACKGROUND

2.1. Similarity-Based-Modeling

Performing system analysis can either be a simple or difficult task depending on the available information to build a model that describes the process dynamics. Access to information is a high value asset, and sometimes access to this information is costly due to economic, computational reasons to mention a few, or simply because the unavailability of historical data or different operating conditions. For these reasons, the use of SBM becomes of relevant support. As defined by (Tobar, Yacher, Paredes, & Orchard, 2011), SBM consists of a non-parametric modeling approach capable of estimating a system's output using historical data and compare it with the actual, measured output once it is available. The main intention of this comparison is to determine if the system is performing in a similar manner as expected by the historical data. If this is not the case, it means that the historical database does not represents all the possible operating conditions, and it this regard, the database must be modified to include all the new information. It is imperative to always keep updating the database when new operating conditions are present. Perhaps, the main advantage of SBM is that it does not require information from the system to formulate a set of equations to explain the system behavior. In other words, SBM estimates the output of the system by comparing the measured input variables with the available information in database, regardless if it is a low or high dimension system. Consider a system described through Equation 1, where x denotes the input of the system while y is used for the corresponding output, and $f(\cdot)$ represents an unknown function.

$$y = f(x), \quad x \in \mathbb{R}^m, \quad y \in \mathbb{R}^p \tag{1}$$

Using the information gathered from the database, the different input and output values must be separated in two different matrices. Equation 2a is used for all the known inputs and equation 2b for the corresponding output.

$$D_i = [x_1\, x_2 \ldots x_n] \in \mathbb{R}^{m\times n} \tag{2a}$$

$$D_o = [y_1\, y_2 \ldots y_n] \in \mathbb{R}^{p\times n} \tag{2b}$$

Since it is possible to relate all the known inputs to their corresponding output value through the unknown function described by equation 1. Thus, the idea behind SBM is that for any given set of inputs x^*, the output y^* can be estimated through a a linear combination of matrix D_o and a weighing vector denoted w. In other words, the estimated output $\hat{y}^*$ is equal to the product between D_o and w, hence $\hat{y}^* = D_o w$. Equations 3 and 4 show how to calculate w. For equation 3 the use of a similarity operator is required, which corresponds to the variable Δ.

$$\hat{w} = (D_i^T \Delta D_i)^{-1}(D_i^T \Delta x^*) \tag{3}$$

$$w = \frac{\hat{w}}{\vec{\mathbf{1}}^T \cdot \hat{w}} \tag{4}$$

According to (Tobar et al., 2011), it is possible to use any similarity operator, however several important characteristics must be present in a SBM approach. Unfortunately, there are not frameworks present in the literature to help the user choose a similarity operator depending on the available on the information. Although the user must consider that for two elements $A, B \in \mathbb{R}^+$ the following conditions must be satisfied for the result of applying the similarity operator :

- $A\Delta B \in \mathbb{R}^+$
- Must be symmetric.
- The maximum value must be reached in $A = B$.
- Monotonically decay with $\|A - B\|$

In this regard, one of the simplest ways to implement the similarity operator Δ is through a saturated triangular function, see equation 5.

$$A\Delta B = \begin{cases} d - \|A - B\| & \|A - B\| \leq d + \epsilon \\ \epsilon & \|A - B\| > d + \epsilon \end{cases} \tag{5}$$

The values of ε and d in equation 5 must be selected accordingly to the available data:

- The value of ε is equal to a very small positive number that ensures $A\Delta B > 0$.
- The variable d is a threshold and its value (greater than 0) is calculated using the variance of the observations.

2.2. Different Uses for SBM

Since SBM consists of a non-parametric modeling technique it can be used in different applications throughout the literature. A very insightful technical document, that explores the diverse uses that can be given to SBM methods is found on (Duch, 2000). In this technical paper, the author covers a great amount of applications, such as: classifiers, ad methods for approximating and associating. For example, neural-like techniques, nearest-neighbors methods, and feature extraction, to mention some. Another example is approached on (Tobar et al., 2011), where the authors propose the use SBM to represent the process behavior in a natural gas power generation plant, and in this way creating a tool suitable for anomaly detection. In their study, the variables included for the modeling were: pressures, temperatures, position of valves, speed of rating parts, among others. Other use of SBM is proposed on (León Olivares, 2012). Similar as before, in this case the author uses SBM as a tool for fault detection on an multivariate industrial process. A different application is presented on (Bhardwaj, Srivastava, & Gupta, 2015). In this case the authors propose the use of patterns and shapes combined with a clustering method based on SBM to predict time series, avoiding the problems associated with autoregressive techniques.

2.3. Battery-Related Concepts

Besides the previously explained general concepts, the following terminology must be understood by a battery user. The first concept is the Depth of Discharge (DoD). The DoD is related to the SOC, since it represents the percentage of how much energy is delivered by the battery. For instance if a fully charged battery is used to a point where the final SOC is 80%, it is said that the DoD is equal to 20%. However, if a battery starts at a 70% SOC, and it is used until it reaches a final SOC of 50%, the DoD would be a DoD of 50%, since the starting point to quantify the DoD is 100%.

Since not always the starting point is a SOC equal to 100%, two concepts become helpful. The first one is called the SOC-swing (SOC-S), and is similar to the DoD. It measures the total difference between the starting SOC value and the lowest value in a cycle. Hence, the SOC-S is reported by just a percentage, for example 20% or 50%. Describing the DoD or the SOC-S is not always enough since this percentage can be calculated starting from any value of the SOC. This is why, defining the swing range (SR) is important. The SR indicates the range in which the SOC-S varies. Using both concepts (SOC-S and SR) is important since the effect on the degradation is different depending on the SR that the battery is used. In other words, if the SOC-S is defined as 50%, the degradation would be smaller if the SR goes from 50%-0% of the SOC than if it goes between [100%-50%] or [75%-25%] (Perez et al., 2017).

When talking about charging and discharging knowing how to interpret a concept known as the C-rate. The C-rate is a factor of the charge/discharge current in terms of the rated capacity expressed in Ampere-hours [Ah]. This factor indicates the amount of current used to charge or discharge the battery. For example, if a battery has a rated capacity of 2 [Ah], and it is discharged with a constant current of 1 [A] then the C-rate is equal to C/2. The C-rate is always expressed in terms of the capacity C. Continuing with the same example, if the battery is discharged using a current of 6 [A], then the the C-rate is equal to 3-C (Wong, Wetz, Mansour, & Heinzel, 2015).

2.4. Battery-Degradation Concepts

According to (Xu, Oudalov, Ulbig, Andersson, & Kirschen, 2018) battery degradation is a non-linear process that depends on both time and the operating characteristics of its use. This process can be influenced by factors such as temperature, charge/discharge cycles, DoD, among others (Balagopal & Chow, 2015). To characterize the degradation process suffered by the battery, several models have been proposed in the available literature, and they can been classified into two main groups: theoretical and empirical. The first group uses the loss of ions and active materials, as well as internal chemical reactions to model the degradation process while the second group uses experimental data (Xu et al., 2018). Some examples of proposed model to characterize the degradation process of Li-ion batteries can be found in (Perez et al., 2017), (May & El-Shahat, 2017), (Stroe, Swierczynski, Stroe, Kaer, & Teodorescu, 2017) and (Perez et al., 2018).

A traditional method to measure how much energy is stored or delivered during a defined time interval (in most of the cases the time interval equals a cycle) is the Coulomb-count method. Since the delivered energy is less in each cycles, the degradation process can be calculated as the ratio of energy delivered in two consecutive cycles (without considering the existence of the self-regeneration phenomena that sometimes occur in Li-ion batteries). Typically the degradation process of Li-ion batteries follow one of two trends, convex or concave depending on the chemistry of the battery (Yang et al., 2017). No matter which of the trends the battery follows, it is possible to calculate the Coulombic efficiency (denoted by the Greek letter η) by dividing the delivered energy at time k, by the delivered energy at time k-1. Although some authors prefer to define it as the ratio between the delivered energy at discharge time k and the stored capacity during charge at the same cycle (Yang, Wang, Zhao, Tsui, & Bae, 2018). Ideally, η should have values close to 1, but since batteries degrade with use (without considering the regeneration phenomena), the highest this value is, the less degradation after one cycle.

Moreover, it is still unknown what is the correct time instant when a Li-ion battery reaches its EOL. However, a rule-of-thumb indicates that a Li-ion battery must be replaced when the delivered capacity reaches an user-defined threshold. The value of this threshold must be between the range of [70%-85%] of the nominal capacity of the battery, since after this point most the energy stored by the battery instead of being delivered, it is dissipated in the form of thermal energy. In other words, the user must decide which percentage will be the desired threshold. Although it is important to mention that regardless if the degradation process follows a convex or a concave trend, that an inflection point will appear towards the EOL, causing η to drop its value. However, this inflection point it is not always present on the information provided by manufacturers on datasheets. On the experiments performed on (Yang et al., 2018) the existence of this inflection point can be noted. This lack of information is what makes difficult the estimation of the EOL of Li-ion batteries, and thus, other techniques must be approached to estimate the RUL of the batteries.

3. METHODOLOGY

3.1. Data sets

This research uses data provided in (Ning, Haran, & Popov, 2003), where the authors cycled a Sony US18650 1.4 Ah Li-ion battery using different discharge rates (1-C, 2-C and 3-C), at a controlled ambient temperature. After 300 cycles, battery capacities were reduced by 9.5%, 13.2% and 16.9% when using 1-C, 2-C and 3-C, respectively. Figure 1 shows the capacity fade results measured every 50 cycles (please note that actual measurements are connected by straight lines in the figure). The same information of Figure 1 can be used to build the associated capacity degradation curve (see Figure 2). Presenting the information of the degradation process by manufacturers in this way is typical because it is simple to understand how the performance of the battery is affected through its lifespan. For instance, it is possible to note on 2 that during the first 50 cycles there is more degradation than in the rest of the cycles. Hence, this characteristic indicates that the initial cycles have a major impact on the rest of life of the battery. Usually, degradation curves are built using obtained data from discharge experiments under controlled conditions (DoD, temperature, C-rates). Although this information is helpful to compare the expected performance of batteries from different brands, it does not suffice to characterize the impact of the degradation when higher currents are used for discharging, or in other words, when the load connected to the battery is variable.

Using the information of Figure 2 is possible to calculate the equivalent η on a cycle-by-cycle basis. For this particular case and since the information regarding the charge process is not available, the η is calculated as the rate between the delivered energy at cycle k and cycle k-1. Figure 3 shows the evolution of the obtained η for the three Li-ion batteries cycled at different discharge current rates. Due to a greater degradation

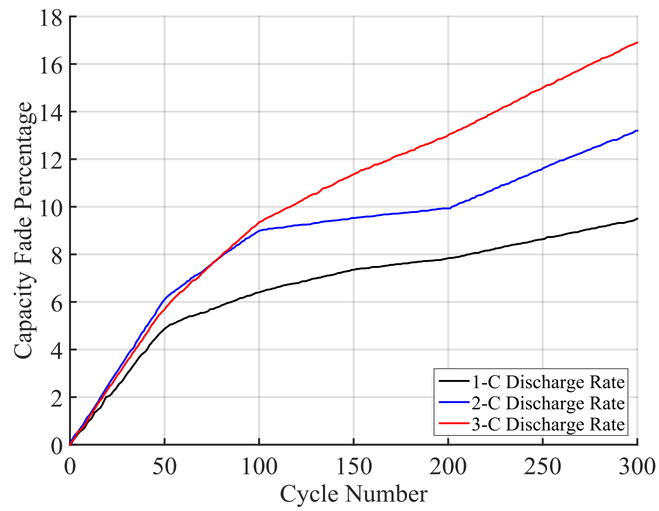

Figure 1. Capacity fade measured every 50 cycles for different discharge current rates. Adapted from (Ning et al., 2003).

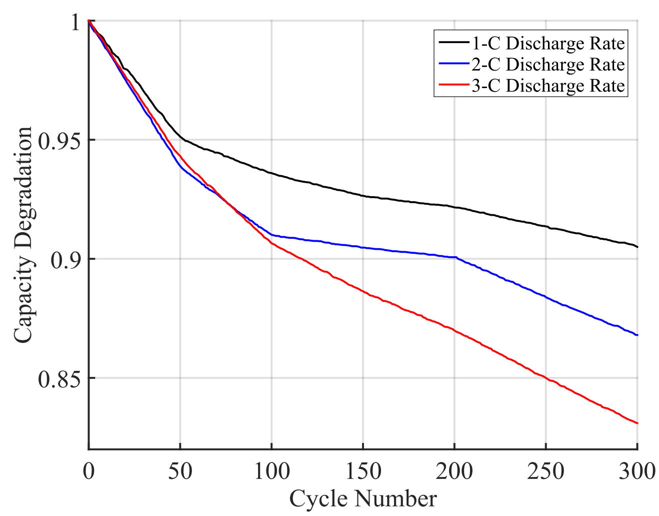

Figure 2. Capacity degradation process for different discharge current rate.

during the first cycles, the value of η has to be lower during those cycles. An important characteristic to note from Figure 3 is that the three curves reach and inflection point and after that the value of η remains practically constant. It is important to keep in mind that these curves only shows the first 300 cycles and that Li-ion degradation curves have another inflection point towards the EOL which is not present in this case. For this reason it would be erroneous to think that η will settle at certain point, when the correct thing is that once the battery reaches that second inflection point, its value will drop again, but as mentioned, this second inflection point is not always presented on the datasheets.

An interesting concept related to η is that it can be characterized using a biexponential expression of the form $y(k) =$

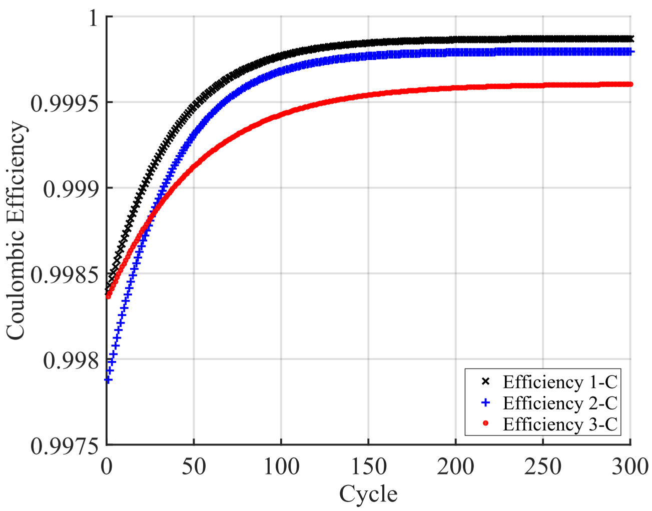

Figure 3. Evolution of the Coulombic efficiency for different discharge currents.

$\alpha e^{(\beta \cdot k)} + \gamma e^{(\delta \cdot k)}$, whithout considering the part of the curve when the second inflection point is present. Table 1 shows the mean value and confidence bounds of the four coefficients that explain the evolution of its value. These values were obtained using the Curve Fitting Tool of Matlab®, and for three cases the sum of squares due to error (SSE) was less than $1 \cdot 10^{-11}$ and the the coefficient of determination (R^2) was equal to 1. Each of the two summands from the previous equation, have a very specific trend. For instance, the summand $\alpha e^{(\beta \cdot k)}$ consists of a straight line which its highest value is given by the value of α at time instant *0*. In other words, the highest value of η is constrained by this result. On the other hand, the other expression, $\gamma e^{(\delta \cdot k)}$ is the one that gives η its final shape, as shown in Figure 3. Note that, that as cycles advance, this expression will increase its value towards zero (since it is a negative term), and the final value of η is given by the term $\alpha e^{(\beta \cdot k)}$.

3.2. Estimating the Degradation Process with SBM

Since the degradation curves shown in Figure 2 illustrate the result of discharging the battery from a 100% SOC to a 0% SOC in each cycle for three different batteries, this section is intended to explain the use SBM to estimate the degradation process of a Li-ion battery, when it is discharged at different current rates during its cycle life. The first step is to determine the required matrices for the SBM approach. In this proposal, the input matrix D_i consists of the following variables: the cycle count, the discharge current, the SOC-S and the average SOC SR. On the other hand, the output matrix D_o is equal to the equivalent η value. Equations 6 and 7 describe the matrices used on this article.

$$D_i = \begin{bmatrix} Cycle & C-rate & SOC-S & \overline{SR} \end{bmatrix} \tag{6}$$

$$D_o = [\eta] \tag{7}$$

For illustrative purposes, in this article the total amount of cycles considered is equal to 1000. In the case of the C-rate, the three different values (1-C, 2-C and 3-C) shown in figure 2 are used. For the SOC-S and its corresponding average, the same eleven cases as described on (Perez et al., 2017). Considering this data, the total amount of rows of D_i is equal to $1000 \cdot 3 \cdot 11 = 33000$.

For the values corresponding to the output matrix D_o, the scaling factors described on (Perez et al., 2017) are used to determine the equivalent η at each cycle for each discharge current. The scaling factors are associated to each of the proposed SR cases, and depending how the battery is discharged the effect of the degradation is different. Furthermore, the scaling factors are different depending on the degradation percentage threshold defined by the manufacturer or the user. Table 2 shows the scaling factors used to calculate the equivalent η.

The main idea of this scaling factors is the following. If a battery is considered to be degraded when its deliverable capacity reaches 85% of its nominal value, then the corresponding scaling factors to column 0.85 must be used. Moreover, if during cycle 1 the battery is discharged at 1-C, with a known η value (extracted from the datasheet) of 0.998407581, and its used with a SR equal to 100-25, then the equivalent η of that cycle will be equal to $0.998407581 \cdot 1.00001354 = 0.998409508$. Using this technique, and the obtained η values from figure 3 is possible to create the output matrix. For this article, this process was performed extracting the η values for each of the three discharge currents of Figure 3, and then each of those values was multiplied by the corresponding scaling factor. Hence, the equivalent η is different for each combination of variables: cycle count, discharge current and SOC-S. Table 3 shows an extract of the input and output matrices constructed with this technique, considering a 0.85 degradation percentage threshold. The first four columns on Table 3 correspond to D_i, while the last column is equal to D_o.

As mentioned before, a total of 1000 cycles were simulated. For each cycle, the SOC-S and SR as well as the C-rate were randomly generated. However, an important restriction was incorporated to the simulation, and it consists that the initial SOC on a any cycle could not be lower than the final SOC of the prior cycle. This was intended to avoid a discharges in between continuous cycles. Figure 4 shows the obtained efficiency values when simulating 1000 cycles. As expected, the trend of the figures is similar to the observed in Figure 3, meaning that the results obtained with the SBM proposal are reasonable and within the reference values.

Furthermore, the distribution of the discharge currents for the

Table 1. Mean value and confidence bounds of the Coulombic efficiency characterization curves.

Coefficient	**1-C**	**2-C**	**3-C**
α	0.9999 $(0.9999, 0.9999)$	0.9998 $(0.9998, 0.9998)$	0.9996 $(0.9996, 0.9996)$
β	$-1.711 \cdot 10^{-8}$ $(-1.79 \cdot 10^{-8}, -1.631 \cdot 10^{-8})$	$-2.415 \cdot 10^{-8}$ $(-2.541 \cdot 10^{-8}, -2.289 \cdot 10^{-8})$	$-3.75 \cdot 10^{-8}$ $(-3.852 \cdot 10^{-8}, -3.647 \cdot 10^{-8})$
γ	$-1.533 \cdot 10^{-3}$ $(-1.533 \cdot 10^{-3}, -1.533 \cdot 10^{-3})$	$-1.996 \cdot 10^{-3}$ $(-1.996 \cdot 10^{-3}, -1.996 \cdot 10^{-3})$	$-1.288 \cdot 10^{-3}$ $(-1.288 \cdot 10^{-3}, -1.288 \cdot 10^{-3})$
δ	-0.02684 $(-0.02685, -0.02683)$	-0.02801 $(-0.02802, -0.028)$	-0.01922 $(-0.01923, -0.01921)$

Table 2. Scaling factors for three degradation thresholds depending on the SR. Adapted from (Perez et al., 2017)

SR	**0.7**	**0.8**	**0.85**
100-0	1.000000	1.00000000	1.00000000
100-25	1.000003	1.00000266	1.00000193
75-0	1.000024	1.00001860	1.00001354
100-50	0.999989	0.99999203	0.99999420
75-25	1.000019	1.00001521	1.00001108
50-0	1.000037	1.00002874	1.00002093
100-75	1.000027	1.00002146	1.00001563
75-50	1.000011	1.00000881	1.00000642
62.5-37.5	1.000008	1.00000620	1.00000451
50-25	1.000043	1.00003347	1.00002438
25-0	1.000054	1.00004184	1.00003047

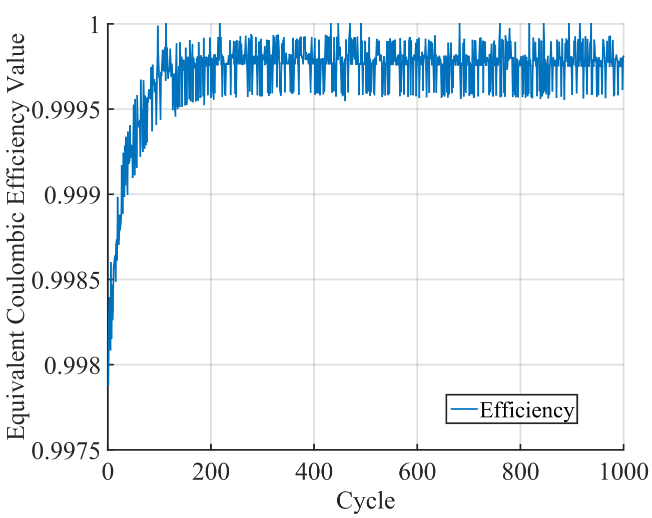

Figure 4. Evolution of η when a battery is discharged at different discharge current rates in each cycle.

Table 3. Example of the some cases of D_i and D_o

Cycle	**C-rate**	**SOC-S**	$\overline{\textbf{SR}}$	$\boldsymbol{\eta}$
1	1	1	0.5	0.998407581
1	1	0.5	0.25	0.998428478
1	2	1	0.5	0.997859108
1	2	0.25	0.5	0.997863609
1	3	0.5	0.25	0.998357377
2	1	1	0.5	0.998447088
2	2	0.25	0.625	0.9979191
2	3	0.25	0.5	0.998364999
3	3	0.25	0.375	0.998408394
3	3	0.25	0.125	0.998414474

1000 cycles is verified with Figure 5, where the discharge current is constrained between 1 [A] and 3 [A].

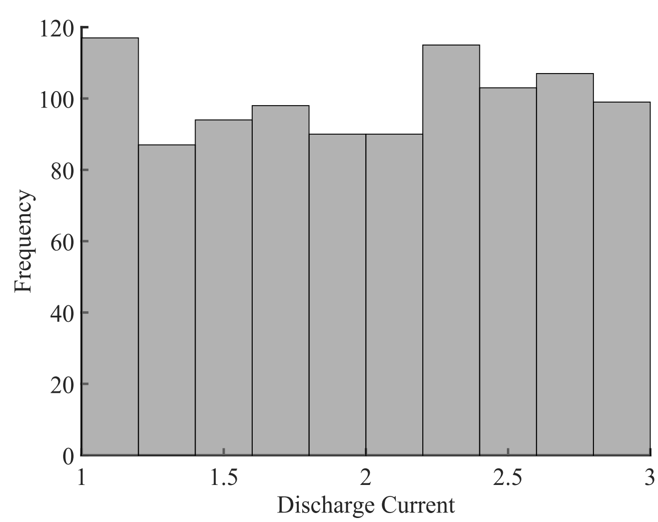

Figure 5. Distribution of the discharge currents for the performed simulation.

Once the distribution of the currents is done verified and the efficiency values of figure 4 follow the trend of the measured data, and the operational SOC policies are set as explained previously it is possible to plot the resulting degradation curve for the simulation.

One major consideration when proposing this method is that the degradation caused when charging the battery is neglected. Since this approach uses information provided by the manufacturer, it is typical that the charging protocol follows the constant current- constant voltage method (CCCV). Another consideration was the temperature. For this article, the temperature was considered constant throughout the lifespan. It is known that temperature has two different effects on Li-ion batteries. One of them being the amount of energy that can be stored and delivered, and the other effect has to do with the characteristics of the degradation curve. Despite this, if a different charging method or different temperatures were to be considered, one of the main advantages of SBM is that the information database can be created considering these characteristics without the need of finding a different type of model.

4. RESULTS

To determine the amount of cycles that the battery will operate before reaching the EOL at the threshold of 85% of its nominal capacity, a Monte Carlo simulation is performed. As mentioned before, the operating conditions during the Monte Carlo simulation include that for each cycle a different discharge current and SOC range were randomly generated. However, the initial SOC of one cycle could not be lower than the final SOC of the previous cycle. This is intended to represent that on consecutive cycles the battery could be charged. For example, cycle 1 can have an initial SOC value of 90% and a final SOC value of 30% using a discharge current of 2 [A], while cycle 2 can be considered using a discharge current of 1.5 [A] and SOC values between 45% and 10%. A total of 25000 realizations were simulated in this case, and for each realization all the C-rates and SOC values are different.

Figure 6 shows the degradation process during the first 300 cycles of one realization of the Monte Carlo simulation and the measured data. As seen, the structure of the degradation process curve follows the trend of the measured data, very similar to the 2-C case, since it is the average value between 1 [A] and 3 [A].

From figure 6 it can be noted that only the curve corresponding to the degradation process at 3-C crosses the established threshold after nearly 250 cycles. If the curves for the degradation processes at 1-C and 2-C were extended for more cycles, the EOL will occur at nearly 980 cycles for the 1-C case, and at almost 450 cycles when discharged at 2-C. Nevertheless these three cases illustrate the EOL when the battery is always fully discharged starting from a fully charged state, while the proposed methodology in this article considers any combination for the SOC range, in each cycle. Figure 7 shows the obtained EOL cycle values after completing the Monte Carlo simulation.

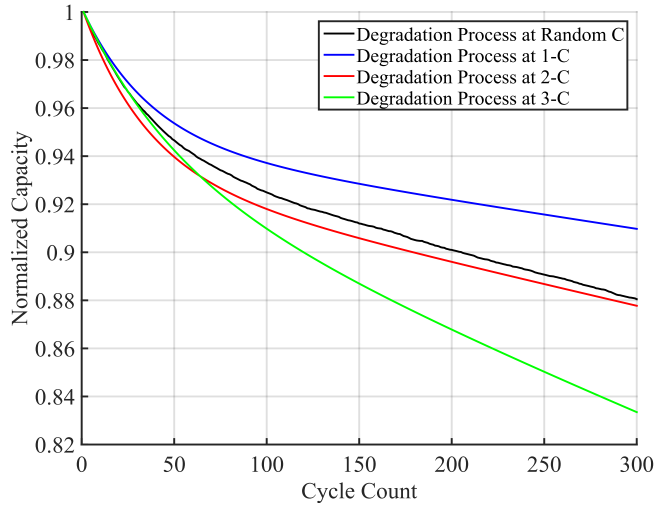

Figure 6. Degradation process for different discharge currents between 1 [A] and 3 [A], and one Monte Carlo realization.

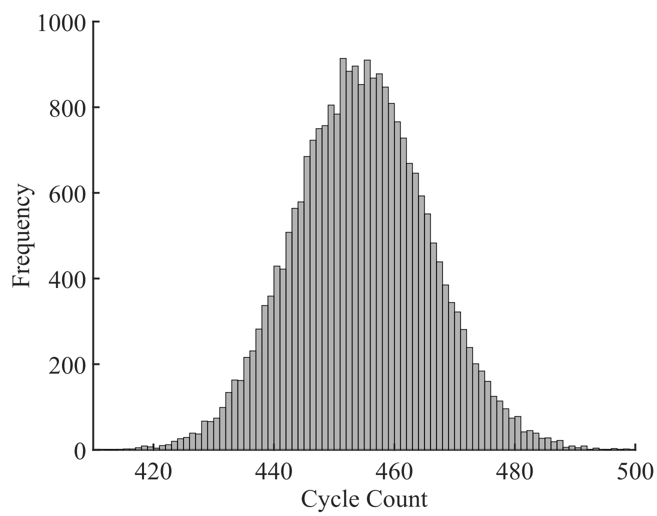

Figure 7. Distribution of the EOL in terms of cycles of a Li-ion battery after a Monte Carlo simulation.

It can be noted that the resulting amount of cycles before reaching the 85% threshold fits a normal distribution, with the following characteristics: $N(454.06, 125.97)$. It is clear that theses results can change for is the battery, if it is discharged among other SOC ranges or discharge currents. What becomes important is that the expected EOL can be estimated after extending the operating region of a Li-ion battery within a manageable uncertainty.

Furthermore, to illustrate the degradation process when a different range of discharge currents are set, a similar procedure is proposed. The procedure is the same as before regarding the generation of the random SOC and discharge current values, however the discharge current is set to values between 2 [A] and 3 [A]. Figure 8 shows the obtained result of one realization of this case. In this case, the degradation process of the simulation shifts to a trend between the 2-C and 3-C case.

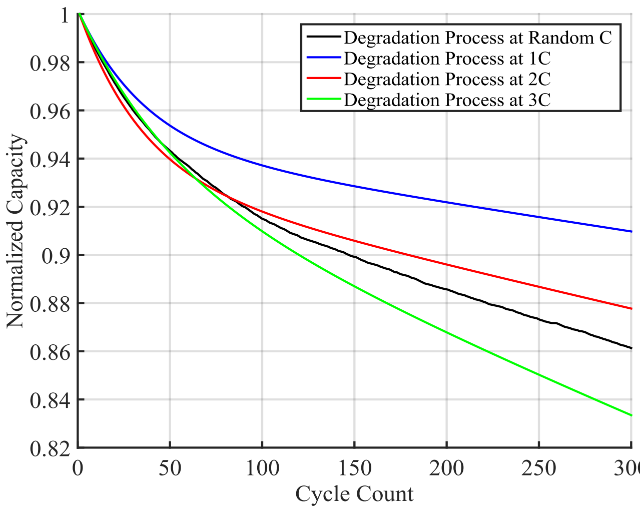

Figure 8. Degradation process for different discharge currents, and one Monte Carlo realization. The random current is constrained between 2 [A] and 3 [A].

These results show that the SBM methodology is capable of characterizing properly the degradation process, when operating at different discharge currents and variable SOC ranges.

5. CONCLUSIONS

A non-parametric methodology that characterizes the degradation process of Li-ion batteries when discharged at various C-rates and SOC-S was proposed. This characterization is based on the calculation of the equivalent η at each cycle. Evidence shows that the evolution of this efficiency can be separated in two exponential coefficients that have different effects on the overall trend.

Using the concepts of C-rate, SOC-S, average SR and η, it is possible to model degradation in a simple manner through interpolation techniques. This method uses the cycle by cycle efficiency to determine an equivalent value for the efficiency depending on the cycle count, SOC limits and discharge current.

SMB is a technique that allows the characterization of the degradation process of a Li-ion battery when used under variable operating conditions. If a Monte Carlo simulation is combined with the SBM method, it is possible to estimate the EOL through the obtained probability distribution function.

The proposed SBM approach can be adapted to different types of Li-ion batteries since the values are normalized, and through the assistance of scaling factors. Also, when new measurements are present they must be compared to the available data to verify if they must be incorporated to the historical dataset.

ACKNOWLEDGMENT

This work has been partially supported by FONDECYT Chile Grant Nr. 1170044, the Advanced Center for Electrical and Electronic Engineering, AC3E, Basal Project FB0008, CONICYT. The work of Aramis Perez was supported by the University of Costa Rica (Grant for Doctoral Studies) and CONICYT-PCHA/Doctorado Nacional/2015-21150121. The work of Francisco Jaramillo was supported by CONICYT-PCHA/Doctorado Nacional/2014-21140201. The work of Vanessa Quintero was supported by the Universidad Tecnologica de Panama and IFARHU (Grant for Doctoral Studies) and CONICYT-PCHA/Doctorado Nacional/201621161427.

REFERENCES

Balagopal, B., & Chow, M.-Y. (2015). The state of the art approaches to estimate the state of health (soh) and state of function (sof) of lithium ion batteries. In *Industrial informatics (indin), 2015 ieee 13th international conference on* (pp. 1302–1307).

Bhardwaj, S., Srivastava, S., & Gupta, J. (2015). Pattern-similarity-based model for time series prediction. *Computational Intelligence*, *31*(1), 106–131.

Duch, W. (2000). Similarity-based methods: a general framework for classification, approximation and association.

Guha, A., & Patra, A. (2018). State of health estimation of lithium-ion batteries using capacity fade and internal resistance growth models. *IEEE Transactions on Transportation Electrification*, *4*(1), 135–146.

Hannan, M. A., Lipu, M. S. H., Hussain, A., Saad, M. H., & Ayob, A. (2018). Neural network approach for estimating state of charge of lithium-ion battery using backtracking search algorithm. *IEEE Access*, *6*, 10069–10079.

León Olivares, A. S. (2012). Detección de anomalías en procesos industriales usando modelos basados en similitud.

May, G., & El-Shahat, A. (2017). Battery-degradation model based on the ann regression function for ev applications. In *Global humanitarian technology conference (ghtc), 2017 ieee* (pp. 1–3).

Ning, G., Haran, B., & Popov, B. N. (2003). Capacity fade study of lithium-ion batteries cycled at high discharge rates. *Journal of Power Sources*, *117*(1-2), 160–169.

Olivares, B. E., Munoz, M. A. C., Orchard, M. E., & Silva, J. F. (2013). Particle-filtering-based prognosis framework for energy storage devices with a statistical characterization of state-of-health regeneration phenomena. *IEEE Transactions on Instrumentation and Measurement*, *62*(2), 364–376.

Perez, A., Quintero, V., Jaramillo, F., Rozas, H., Jimenez, D., Orchard, M., & Moreno, R. (2018). Characterization of the degradation process of lithium-ion batteries when discharged at different current rates. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 0959651818774481.

Perez, A., Quintero, V., Rozas, H., Jaramillo, F., Moreno, R., & Orchard, M. (2017, April). Modelling the degradation process of lithium-ion batteries when operating at erratic state-of-charge swing ranges. In *2017 4th international conference on control, decision and information technologies (codit)* (p. 0860-0865). doi: 10.1109/CoDIT.2017.8102703

Stroe, D.-I., Swierczynski, M., Stroe, A.-I., Kaer, S. K., & Teodorescu, R. (2017). Lithium-ion battery power degradation modelling by electrochemical impedance spectroscopy. *IET Renewable Power Generation*, *11*(9), 1136–1141.

Tobar, F. A., Yacher, L., Paredes, R., & Orchard, M. E. (2011). Anomaly detection in power generation plants using similarity-based modeling and multivariate analysis. In *American control conference (acc), 2011* (pp. 1940–1945).

Wong, D., Wetz, D., Mansour, A., & Heinzel, J. (2015). The influence of high c rate pulsed discharge on lithium-ion battery cell degradation. In *Pulsed power conference (ppc), 2015 ieee* (pp. 1–6).

Xu, B., Oudalov, A., Ulbig, A., Andersson, G., & Kirschen, D. (2018). Modeling of lithium-ion battery degradation for cell life assessment. *IEEE Transactions on Smart Grid*, *9*(2), 1131 – 1140.

Yang, F., Wang, D., Xing, Y., & Tsui, K.-L. (2017). Prognostics of li (nimnco) o2-based lithium-ion batteries using a novel battery degradation model. *Microelectronics Reliability*, *70*, 70–78.

Yang, F., Wang, D., Zhao, Y., Tsui, K.-L., & Bae, S. J. (2018). A study of the relationship between coulombic efficiency and capacity degradation of commercial lithium-ion batteries. *Energy*, *145*, 486 - 495. doi: https://doi.org/10.1016/j.energy.2017.12.144

BIOGRAPHIES

Dr. Aramis Perez received his B.Sc. degree and Licentiate degree in Electrical Engineering from the University of Costa Rica. He received his master degree in Business Administration with a General Management Major from the same university. He also received the Doctorate in Electrical Engineering degree from the University of Chile. Currently he is a Research Fellow at the Fault Diagnosis and Failure Prognosis Laboratory and the Energy Center of the University of Chile. Also,he is a Professor at the School of Electrical Engineering at the University of Costa Rica. His research interests include parametric/non-parametric modeling, system identification, data analysis, and manufacturing processes.

Francisco Jaramillo received the B.Sc. degree in Electronics Engineering from Universidad de La Frontera, Temuco, Chile, in 2009. Currently he is a doctorate candidate and a researcher at the Fault Diagnosis and Failure Prognosis Laboratory at the University of Chile . His research interests include machine learning, control systems, and estimation and prognosis based on Bayesian algorithms with applications to nitrogen removal in pilot-scale Sequencing Batch Reactors for Wastewater Treatment Plants.

Vanessa Quintero received her B.Sc degree in Electronics and Telecommunication Engineering at the Universidad Tecnologica de Panama (2007). Currently she is a doctorate candidate and a researcher at the Fault Diagnosis and Failure Prognosis Laboratory at the University of Chile. Her research interests include estimation, prognostics with applications to battery and protocols design.

Dr. Marcos E. Orchard received the B.S. degree and a Civil Industrial Engineering degree with electrical major from Catholic University of Chile. He also received the M.S. and Ph.D. degrees from The Georgia Institute of Technology, Atlanta, GA, USA. He is currently an Associate Professor with the Department of Electrical Engineering, and the head of the Fault Diagnosis and Failure Prognosis Laboratory at the University of Chile. His current research interest is the design, implementation and testing of real-time frameworks for fault diagnosis and failure prognosis, with applications to battery management systems, mining industry, and finance.