Development of a voltage curve prediction model for lithium-ion battery based on destructive tests

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Abstract. With the increasing development of portable devices, research on mobile power sources have been an important goal. Thus, the improvement on their safety, energy density and degradation rate is the current challenge of different researchers. The present work seeks to develop an algorithm, based on artificial neural networks, to predict the voltage curve of a lithium-ion battery based on destructive tests. It was found that the developed system can define the condition of the battery in the test and generates voltage curves that allow the estimation of the battery’s charge and it’s charging time.

Keywords. Lithium-ion Battery, SoC, Mobile energy, Artificial Neural Network.

1. Introduction

The rising of social media and smartphone apps leading to a growing demand in mobile energy, shows a change in social habits over the past decade. This scenario generates pressure on the development of mobile energy storage, which meets the requirements of high load capacity and autonomy.

The batteries based in Ni-Cd-technology, common until the end of 1990, presented some problems like charge’s memory, low energy density, and toxicity. These problems led this technology to be replaced by a lithium-ion-based system. Lithium-ion batteries, most commonly used in electronic equipment today, have higher energy density than other batteries, which makes them lighter and efficient [1]. Although their cost is higher than Ni-Cd batteries, they are more environmentally friendly and don't show charge's memory problems.

But even with better efficiency, today's batteries still can suffer from their operating environment. Thus, while using a battery in high-temperature environments favors a deterioration of battery's health (leading to a reduction in its useful life) a very low temperatures condition tend to drain its energy faster [2]. Other aspects related to the conditions of battery use, such as deep discharges and accelerated battery charging, may lead to rapid degradation [1-2]. Thus, a degraded battery has less capacity to hold the charge and therefore discharges faster, reducing its autonomy.

The effect of low charge capacity is reflected by large variations in battery’s voltage [2-5], leading to its nominal voltage to reaches the voltage limit for charging and stating that is fully charged. The opposite occurs in its discharge process, where it presents a rapid drop in voltage levels until reaching the limit of the depth of charge.

The evolution of battery voltage over time or simply battery state of health (SoH) is an important parameter for describing battery condition, and assists in estimating the number of charges and discharge cycles that the battery can still withstand [6].
Although there are models developed to estimate battery health, it presents high computational complexity (seen the nonlinear behavior of SoH) [7] and requires invasive battery measurements. Thus, the purpose of this work is to perform, through destructive lithium-ion battery charging and discharging's tests, to monitor both voltage and temperature. This information will be organized in such a way as to generate a database about the behavior of batteries over their lifetime. This database will provide a history of cases in which an artificial neural network will use to predict the battery voltage curve as a function of its temperature.

2. Materials and Methods
A measuring system has been developed to estimate the lifetime of a battery through consecutive charge and discharge cycles. The system consisted of an electronic and a computer control part.

2.1. Electronic Circuit
The electronic circuit is based on a dual feedback analog central core, which controls the load phases with current and constant voltage. To this core were added several modules that, combined with an Acquisition and Control Unit (ACU), allow the system to perform a long-term automatic test, enabling to better understand the behavior of lithium-ion batteries.

The block diagram of figure 1 shows the components of the proposed system. Three blocks stand out in the diagram: the load circuit (DC), the data acquisition and drive module (A/D) and the microcomputer where the supervision and control software (μ) operates.

![Figure 1. Test System Block Diagram.](image)

The VBMAX voltage (charge limit voltage) has been set to 4.1 volt, the value commonly used by the smartphone battery industry. The voltage VBMIN (discharge limit voltage) has been set to 3.1 volt. This voltage value is described as the voltage at which the battery loses on average 95% of its initial charge and is used by the software to control the end of the discharge step.

The value of the charging current at the end of the charging cycle (ICMIN) shall be equal to 1/10 of the ICMAX current, and when reached indicates the end of the charging phase. At this stage, the battery typically reaches 95% of its maximum charge. The last two parameters (VBMIN and ICMIM) are hardware adjusted through LabView software. To not compromise battery life and prevent overheating, the initial discharge current (IDMAX) has been adjusted to correspond to a discharge rate of 0.5C (C-rate is the current required to charge a battery at 1 hour, regardless of the nominal charge capacity of the battery). Thus the discharge current was set to be equal to 2.5 A so that the value of the RD resistor used for battery discharge was equal to VBMAX / IDMAX or 1.64 Ω.

As a nominal capacity of the test batteries is 5 000 mA/h, a load current (ICMAX) was set to 2 A. This ensures that this current does not reduce battery life.
As illustrated in figure 1, the voltage \( V_B \) between the battery terminals is permanently supervised by the A/D, both during the charging phase (negative terminal connected to \( C \)) and the discharge phase (negative terminal connected to \( D \)). The relay RL1, which transfers load contact \( C \) to discharge contact \( D \), is controlled by a latch circuit that is set by the CC at the end of the saturation phase (i.e., when \( i_C = I_{C\text{MIN}} \)) and reset starting from the output. CHARGE from A/D at the end of the unloading phase (i.e., when \( V_B = V_{B\text{MIN}} \)). The battery discharge current will only circulate through \( R_D \), as the \( SAD \) \( V_B^+ \) and \( V_B^- \) inputs are characterized by very high impedances.

The A/D has a second digital output, END, which commands the end of the test by triggering RL2, and a COUNT digital input that is connected to the latch output signal and used by the software to account for charge/discharge cycles.

Also present in the circuit is a thermoresistor for reading the battery temperature. The software is responsible for supervising the temperature, causing the system to shut down automatically if the circuit overheats. Battery temperature is also stored for use as a neural network parameter.

A timing circuit was incorporated into the circuit allowing the reading of battery voltage in an open circuit. In this way, the voltage can be measured without the influence of the charging circuit and internal battery inductance at the end of each full charge cycle.

The communication between hardware and software is made from an Acquisition and Control Unit (UAC), whose block diagram is illustrated in figure 2.

2.2. Digital controller and acquisition

The software was developed in LabView language and has the function of storing the test data and controlling the battery charge/discharge system through the Acquisition and Control Unit (ACU). The ACU receives the voltage (measured in open and closed circuit) and battery temperature from the circuit. The software stores this data in .CSV format. The test takes place in 3 steps: charging, open circuit, and discharge. By default, the program starts in charge mode and switches to open circuit mode at the time the end of the constant voltage charging period is identified.
The program is responsible for controlling the discharge by initiating a new charging cycle, open-loop measurement, and discharge. This control occurs through digital signals sent at the end of each process. Thus, the software is responsible for storing data and controlling the charge and discharge of batteries automatically.

As mentioned earlier, voltage (open and closed circuit) and temperature data are stored in .CSV format for later reading by the neural network. In addition to this data, full load data is also stored at the end of each cycle. This data is calculated by the software using the battery voltage data.

The software is also responsible for ensuring circuit safety. This is done through the temperature data, where if higher than 50 °C, the circuit is turned off and it is informed on the program screen that the circuit has been interrupted due to the high temperature.

Figure 3a shows a test been executed with a used battery and in the figure 3b, the screen of the software used for the prototype charge/discharge circuit tests.

![Figure 3. Software screen.](image)

2.3. Neural Network Analysis
For the prediction of the batteries curves voltage from its superficial temperature, an artificial neural network (ANN) was developed.

An ANN is a computer algorithm inspired by the human brain information processing. In the biological structure, a neuron receives signals (synapses) from other neurons and propagated it (or not) if this signal is higher than an activation potential. The interaction of all neurons make possible to the brain to solve day a day complex problems, like face recognition.

In an artificial neural network, the information processing is similar. Some inputs representing different signals enter an artificial neuron that processes this information and output response. Equation 1 represents the output of an artificial neuron \( y_k \) with respect to all \( x_i \) inputs and its related weights \( w_{ki} \).

\[
y_k = \varphi \left( \sum w_{ki} x_i + b \right)
\]

The \( b \) is a bias factor and \( \varphi \) the function represent de activation function which can be linear, sigmoidal or hyperbolic.

Like the functioning of the human brain, an ANN learns through a training process. This process is characterized by the presentation of inputs to the ANN and computing the error between its output and a real (known) value. This difference in the output e the real value is used to adjust all the neuron’s weight.

In the present work, it was used the ANN named Multilayer-Perceptron (MLP) network with a typical topology shown in the figure 4.
This ANN is known to be a universal approach. It is composed of (at least) 3 neuron's layers linked together. It is trained by a backpropagation algorithm (the output error is propagated from output to input) and can use to solve any nonlinear problem.

To help with the problem of battery’s characterization through temperature measurements, it was developed two ANN. The first one was set to predict the electric tension one step ahead, and the second one identifies the state of the charger cycle (a charge, discharge or open circuit).

The algorithm was developed in MatLab and it was designed to carry out the following tasks:

- Read data from the tests (voltage and temperature)
- Normalize inputs
- Realize attribute extraction from temperature data
- Run ANN1 and ANN2

3. Results

A laboratory test was performed with a lithium-ion battery in its middle lifetime. Measurements were performed over 3 uninterrupted weeks, and in this period 110 Mb of data was generated. In figure 5 it is possible to observe part of the measurements during the destructive tests.

Once the experimental data would be intended for being used on the ANNs training, they were divided into three distinct groups. The first one, containing 70% of the data, was selected for the neural’s network’s training. The second group (15%) for validation and one third (15%) for testing. Thus, it was
possible to infer the ANN’s generalizability capacity, as they will be tested with different data from those used by their training.

To serve as ANN’s input it was used the following attributes: The gradient’s temperature, the temperature 50 minutes earlier and the temperature 100 minutes earlier. As a target, the first ANN gets the voltage 10 minutes ahead, and the second ANN for the state of the battery charge phase, which was encoded as follows: 0 – Charge; 1 – Open circuit; 2 – Discharge.

To optimize the ANN developed, it was conducted a systematic analysis of the number of neurons in the ANN’s layers, where the ANN’s output was compared with the true voltage value and an error were calculated. As a result, it was defined that the ANN1 and ANN2 give better predictions with 18 neurons in the first layer and 5 neurons in the second layer.

In figure 6, it is possible to observe the prediction of the ANN1 and the real voltage value.

![Figure 6. The curve in red is the ANN prediction and in blue the voltage measure within the experimental tests.](image)

It is clear that although the the results generated by the ANN have a discrepancy with respect to the measured voltage, it can be used to estimate the SoC (State of Charge) of the batteries.

4. Conclusions

It was developed an automatic measurement system of charge/discharge battery cycles, which made it possible to conduct tests on ion-lithium batteries. The initial tests indicated that would be possible to develop an algorithm to predict the voltage output of a battery-only measuring its temperature while the test was conducted.

To conduct a future battery non-invasive test, an artificial neural network was developed to predict a voltage curve.

The preliminary results show that the prediction made by the ANN developed assembles the voltage curve measure. So in the future, it will be possible to investigate some batteries’ property, as charge and period of charge without the need for carryout invasive tests.

It also opens the possibility of investigating the level of degradation on ion-lithium batteries and describe its durability.

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