A NEW END-OF-LIFE ESTIMATION METHOD FOR LEAD-ACID BATTERY USED IN OFF-GRID PV PLANT BASED ON LABORATORY DATA

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Abstract

Photovoltaic (PV) systems have been widely used as a cost-effective solution to provide electrical energy to remote rural villages. The reliability of a PV plant depends on energy storage reliability. Lead-acid batteries have a large market share of standalone PV energy storage, due to their cost-benefit ratio. As remote PV plants operate for months without human intervention, there is a need for detecting the End-of-Life (EoL) of batteries. Although there are several algorithms for this purpose, most of them were designed for indoor laboratory use. A cost-effective solution for monitoring hundreds of batteries in a rough remote environment of a PV plant is crucial.

This paper presents a simple, robust and non-invasive EoL estimating method based on a modified version of a dV/dt algorithm. The proposed method was applied on almost a hundred flooded lead-acid batteries, arranged in 32 sets of three elements each. Each set was tested during 26 months, being interrupted when the EoL point was reached. Basic external parameters, such as voltage and current, were monitored once per minute and these data were used to test and validate the algorithm. Results show that it is possible to predict EoL proximity weeks in advance, although care must be taken when using dV/dt as a prediction tool. A Battery Monitoring System using a dV/dt algorithm is also presented.

Introduction

The Rural Electrification Program "Light for All" is a program started by the Brazilian government, which guarantees electrical energy supply to any house, even if located at a remote small village[1]. For such rural and isolated communities, renewable energy sources, such as PV, integrated with battery energy storage systems are economically cost-effective compared to other alternatives[2].

Whereas grid-connected energy supply depends mainly on transmission system reliability, off-grid energy supply through PV, on the other hand, depends on the energy storage system adopted. Despite all the new energy storage technologies, lead-acid batteries remain the most used in off-grid PV systems because they have the best cost-benefit ratio. According to Avicenne, lead-acid batteries had more than 70% of worldwide battery market share in 2018[3]. Besides, considering the adverse conditions to which the battery is submitted in off-grid PV system applications, a reasonable option is to adopt the Stationary Flooded Tubular Lead-acid Battery (OPzS battery), which is a flooded stationary battery with tubular positive plates that offer a high cycling expectancy due mostly to the positive grid lead alloy (which contains antimony) and the retention sleeves for the active lead paste.

For these remote PV power plants using battery energy storage systems, due to the time it takes to get spare parts, and due to the maintenance cost, it is essential to have a way to predict the End-of-Life (EoL) of batteries some weeks in advance. There is a need for a non-invasive, simple, robust and cost-effective solution.

Throughout the last ten years, several methods to predict a battery's EoL have been proposed[4, 5]. However, most of them are methods conceived for laboratory use and on a small-scale, not being ready for field application with hundreds of batteries operating in a rough environment. Another flaw is that papers describing these methods rely on a small number of test cases, giving no clear information about its robustness for adverse conditions. This is especially critical for lead-acid batteries, since this type of battery has more random behaviour than some other types.

In this context, CPQD is conducting a Research and Development (R&D) project supervised by the National Electrical Energy Agency (ANEEL – Brazil) and sponsored by Guascor do Brasil, with the main objective of developing an algorithm that estimates the proximity to EoL of OPzS lead-acid batteries in off-grid PV system applications. The algorithm will be implemented in a battery monitoring system in order to identify early failures in the batteries so that preventive and corrective maintenance, besides replacement, may be planned in advance. The hardware that constitutes the monitoring system is under development.

Statement of the Problem: A simple EoL Estimation Method

Battery degradation due to aging and operating conditions is measured by its State of Health (SoH). At any given time k, SoH of a battery is given by the ratio of its actual capacity C_k and the manufacturers 100% rated capacity C_N. That is,

$$\boldsymbol{SoH_k = \frac{C_k}{C_N}} \tag{1}$$

Measurement of C_k is obtained through full recharge-discharge testing procedure of the battery. Therefore, the measurement must be done with the battery disconnected from the plant. For the safe lifespan of a battery, said End-of-Life (EoL) is given when SoH reaches a certain value. In this project, 0.8 was used as the EoL limit for SoH, given that it is a generally accepted value[4], and to be conservative for safety reasons.

Since direct measurement of C_k, and therefore SoH, is unpractical during a battery's normal operation, and since predicting the safe lifespan of a battery is critical to several applications, there have been several studies on this subject, with many prediction algorithms being developed[4, 5]. The common approach for battery parameters estimation, e.g. SoH, is based on equivalent circuit models that are mathematically represented by state space equations[6].

However, despite the quality of such algorithms, there is still a great concern on how they can be implemented in large scales, in an open and electrically noisy environment, such as an off-grid PV plant. According to Dr. Preger, from Sandia National Labs[6]:

> *"A variety of tools and tests for battery failure detection have been developed in laboratory settings. However, translating these lab-scale diagnostic systems to fielded technologies is not straightforward. For example, in the lab, one can monitor various subtle electrical outputs from a single cell to determine if it is about to fail. [...But] instrumenting large energy storage systems could be prohibitively expensive when you have thousands of cells in the case of EV batteries and even larger numbers of cells in grid storage systems. Furthermore, is it still possible to detect these signals when using [cheap] field devices rather than a precision instrument in a lab? Translating many of the creative diagnostic approaches developed in the last few years from the lab to the field remains a daunting challenge."*

Although Dr. Preger used these words to describe Li-Ion battery types, this is also true for every type of battery. For lead-acid batteries, unlike the ones used in backup systems operating most of the time with 100% of State-of-Charge (SoC), the SoC and SoH estimation in off-grid PV systems is a hard task, due to the uneven cycling regime and the rare full recharge of the batteries.

Estimation method requirements

In fact, a good EoL estimation method for field use has different requirements from the ones for laboratory use. For laboratory use, an algorithm is as good as its ability to track the actual SoH value[7]. Nevertheless, for field use, an exact tracking of SoH is not essential. Instead, it is more desirable to have a reliable estimation of EoL proximity, with some weeks in advance, in a simple and robust way. An EoL estimation method for field use must, therefore, fulfill the following requirements:

- Detect EoL some weeks in advance even if the exact SoH estimation is unknown. Although an exact (or approximate) SoH value could be helpful to indicate EoL proximity, estimating this exact value can be a hard, expensive and complex task.

- Be simple, requiring no special or complex set-up inside the PV power plant in order to allow for hundreds or thousands of batteries.

- Be non-invasive, allowing measurements without interrupting the battery's continuous operation. Most of the existing algorithms, even without requiring full recharge-discharge tests, are invasive and the battery must be disconnected from the system in order to allow the measurements.

- Work in a rough environment: electric noise from switching operation of the power inverter or simply from high current amplitude variation can affect measurements. Besides noise, in Brazil, outdoor temperatures can vary from 4°C at night, to 50°C at noon[8].

- Be robust, dealing with a wide variety of operating conditions. Besides that, the actual operating condition is unknown – battery can be in low-SoC or high-SoC conditions for a very long time.

- Be reliable, since most PV plants will be installed in remote locations they will work without human presence for many months.

- Be low cost, working with cheap devices and equipment, in order to allow monitoring of large numbers of batteries simultaneously.

Experimental Data

The lead-acid battery, despite its good cost-benefit ratio, presents a challenge for any prediction method. Due to its internal composition, its ageing behaviour is quite a bit more random than many other types of batteries (e.g., alkaline, lithium-ion). To overcome this, a stressing process on a set of 96 batteries, from two manufacturers (A and B), was carried out in order to get accelerated ageing data from them[8].

Batteries were arranged in 32 sets of 3 elements each. Each pair of sets, from manufacturers A and B, was submitted to a given type of accelerated ageing test, under different conditions, covering the main factors of a flooded lead-acid battery's degradation: stratification, sulfation, corrosion, and active mass degradation. The tests reproduced real operating conditions such as temperature, depth of discharge and state-of-charge in cyclic operation.

The tests lasted for 26 months or until the set entered into EoL condition, evaluating the battery's behaviour throughout its lifetime. For each set, basic data – voltage, current and temperature – was recorded every minute. Cyclic stressing tests were alternated, from time to time, with capacity tests, in order to make direct measurement of SoH. For these times-series data, temperature was kept constant at a high value, in order to obtain accelerated ageing. A further development is going to consider the temperature.

Table 1 shows a brief description of each test type, and the results obtained for each set. Preliminary results of the lab tests were presented at Battcon 2016 in the paper entitled "Ageing Evaluation of Lead-Acid Battery Used in Off-Grid Photovoltaic System"[9].

Table 1. Types of cyclic tests

Set	Test	Expected degradation	EoL	
			A	B
1	Discharge Profile	Not Applicable (NA)	NA	NA
	Recharge Profile	Not Applicable	NA	NA
2	Phase A: Partial cycling between 25% and 55% SoC at 40°C	Sulfation, stratification and corrosion	Yes	Yes
	Phase B: Partial cycling between 75% and 100% SoC at 40°C			
3	Phase A: Partial cycling between 25% and 55% SoC at 50°C	Sulfation, stratification and corrosion	Yes	Yes
	Phase B: Partial cycling between 75% and 100% SoC at 50°C			
4	Cycling test around 10% SoC	Sulfation and stratification	No	Yes
5	Cycling test around 40% SoC	Sulfation and stratification	No	Yes
6	Decentralized Rural Electrification (DRE) Cycling test	Sulfation, stratification and active mass degradation	No	No
7	Partial cycling between 85% and 100% SoC at 40°C	Corrosion	Yes	Yes
8	Partial cycling between 70% and 85% SoC at 40°C	Sulfation	Yes	No

Table 1. Types of cyclic tests				
Set	**Test**	**Expected degradation**	**EoL**	
			A	**B**
9	Partial cycling between 55% and 70% SoC at 40°C	Sulfation and stratification	No	Yes
10	Partial cycling between 40% and 55% SoC at 40°C	Sulfation and stratification	No	Yes
11	Partial cycling between 85% and 100% SoC at 50°C	Corrosion	Yes	Yes
12	Partial cycling between 70% and 85% SoC at 50°C	Sulfation	Yes	Yes
13	Partial cycling between 55% and 70% SoC at 50°C	Sulfation and stratification	No	Yes
14	Partial cycling between 40% and 55% SoC at 50°C	Sulfation and stratification	No	Yes
15	Cycling based on hybrid system deployed by Dresser-Rand Guascor in Brazil	Sulfation	No	Yes
16	SoC estimation	Not Applicable	NA	NA

Outlining an EoL estimation algorithm: dV/dt

For the EoL estimation, some algorithms from different technical papers were selected and adapted in order to be suitable for remote field application. The selection was based on the aforementioned criteria, mainly simplicity and non-invasiveness. The algorithms were tested on datasets obtained with the 14 types of ageing tests according to Table 1.

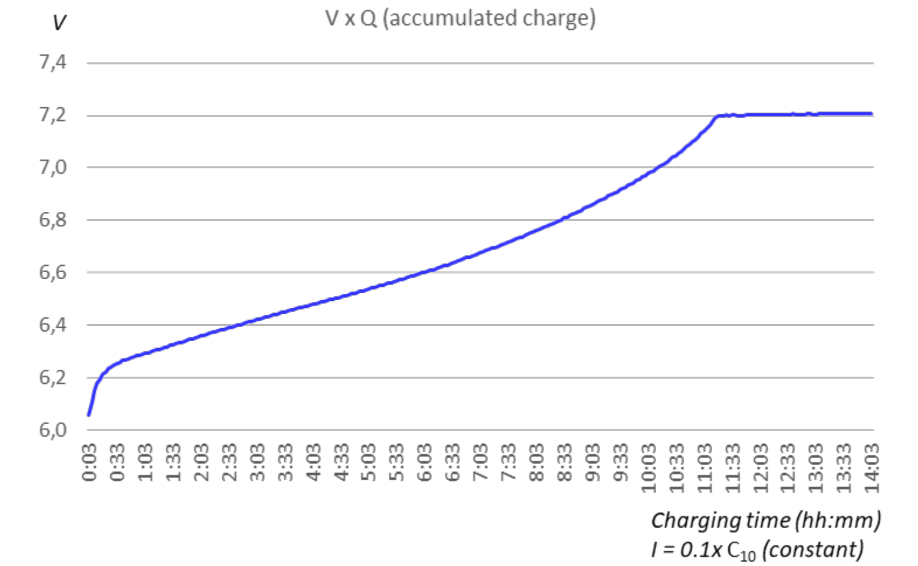
From the tested algorithms, a proposed modified version of change of voltage rate (dV/dt) has presented the best performance for many of the test sets. The logic for the dV/dt technique is quite simple: as a battery degrades, its internal capacity decreases, and therefore, for a given charging current I, the battery will reach a full state-of-charge in less time. That is, for a degraded battery, dV/dt is higher than for a new one. The same occurs for discharging, when the degraded battery reaches a low SoC faster than when it was new.

For practical field use, however, there are some limiting factors. First, the recharging current (I) depends on the solar incidence on PV panels, and can be rather variable in cloudy days. On the other hand, for the discharging phase, the current depends on the consumer's demand. So both can be totally random variables.

A second problem is that the voltage (V) versus the accumulated charge (Q) curve is not linear. Figure 1 shows the V *vs.* Q curve obtained during an initial test for a battery with 100% SoH. The x-axis is the time elapsed since the beginning of the recharge phase. Since recharging current, in this case, is constant (0.1 x C_{10}), the x-axis is equivalent to the accumulated charge. The voltage refers to the set's total voltage, that is, the three elements connected in series. It can be seen in Figure 1 that the $V(Q)$ relationship is not linear. When the battery is in its low SoC (at the beginning of the curve), dV/dt is higher than in the middle of the curve. On the other hand, when the battery is reaching high SoC (V > 7.0 volts), dV/dt rises again, being higher than in the middle part of the curve.

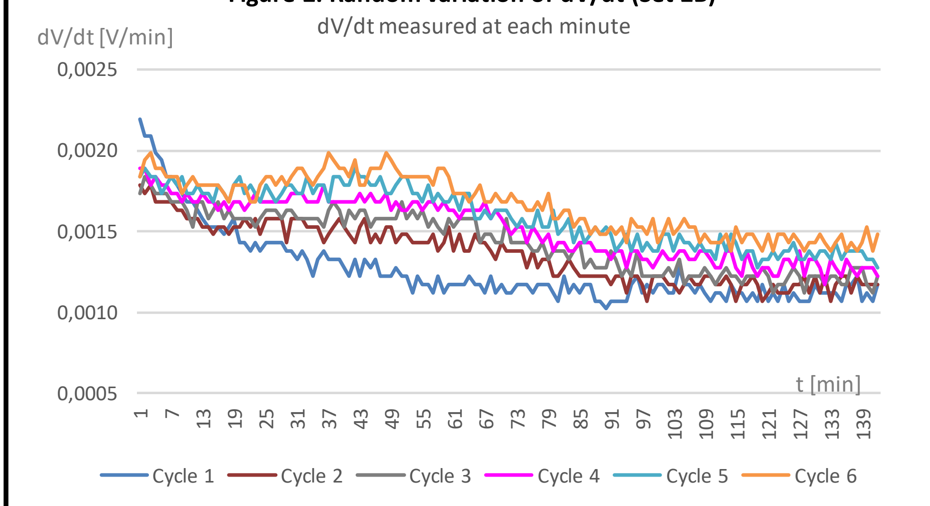
Therefore, because of these nonlinearities, special care must be taken when comparing the actual dV/dt and the past dV/dt: they must refer to the same point on the VxQ curve. This issue is particularly difficult to solve, considering that the voltage balance in a regular normal operating day is totally random: in one given day, the battery can be in low SoC, that means, in the lower part of $V(Q)$ curve; and on another day, the battery can be in the middle part of $V(Q)$. If this occurs, it would be hard to compare dV/dt measured on these two days.

Figure 1. V *vs.* Q curve, during 10 hours discharge rate (C_{10}) - new battery (Set 2B)



A third concern is about the voltage stability and, therefore, the dV/dt stability, within a given battery. Figure 2 presents dV/dt measured at each minute, for the first 140 minutes of recharging phase, within 6 recharging cycles (set 2B). It is noteworthy that dV/dt presents, for short time, a random behaviour. Possibly this behaviour is related to the random movement of ions inside a lead-acid battery, causing such drift

Figure 2. Random variation of dV/dt (Set 2B)



Using dV/dt as a prediction tool in a PV power plant must take into account all these limitations. The following precautions were taken in our approach:

- Data are collected only within the linear region of $V(Q)$ curve, that is, for voltages between 6.3 V and 6.9 V.

- dV/dt is evaluated not as an instantaneous value but within a sliding window of 15 minutes.

The variable nature of current I is compensated according to:

$$dV/_{dt} = \frac{\Delta V}{\Delta t} \cdot \frac{I_0}{I_{avg}} \tag{2}$$

where Δt is the 15-minute window, I_0 is the nominal current of battery and I_{avg} is the average current within the measuring window.

The valid values of dV/dt measured for each 15 minute window according to equation (2) are averaged to obtain the daily value. The daily values are then translated into an EoL indicator, by comparing them to a given threshold. For research purposes, both recharging and discharging data was considered.

Results and Discussion

Figure 3 presents the results of the proposed dV/dt algorithm applied to different battery data sets. For each graphic, the y-axis represents the daily averaged dV/dt (mV/min) and the x-axis represents the 100% timespan of useful battery life, i.e., the last point of x-axis is the EoL point. Each x-axis point is the reading for one day. The curve in blue is the dV/dt for the recharging phase, whereas the red curve is the dV/dt measured for the discharging phase.

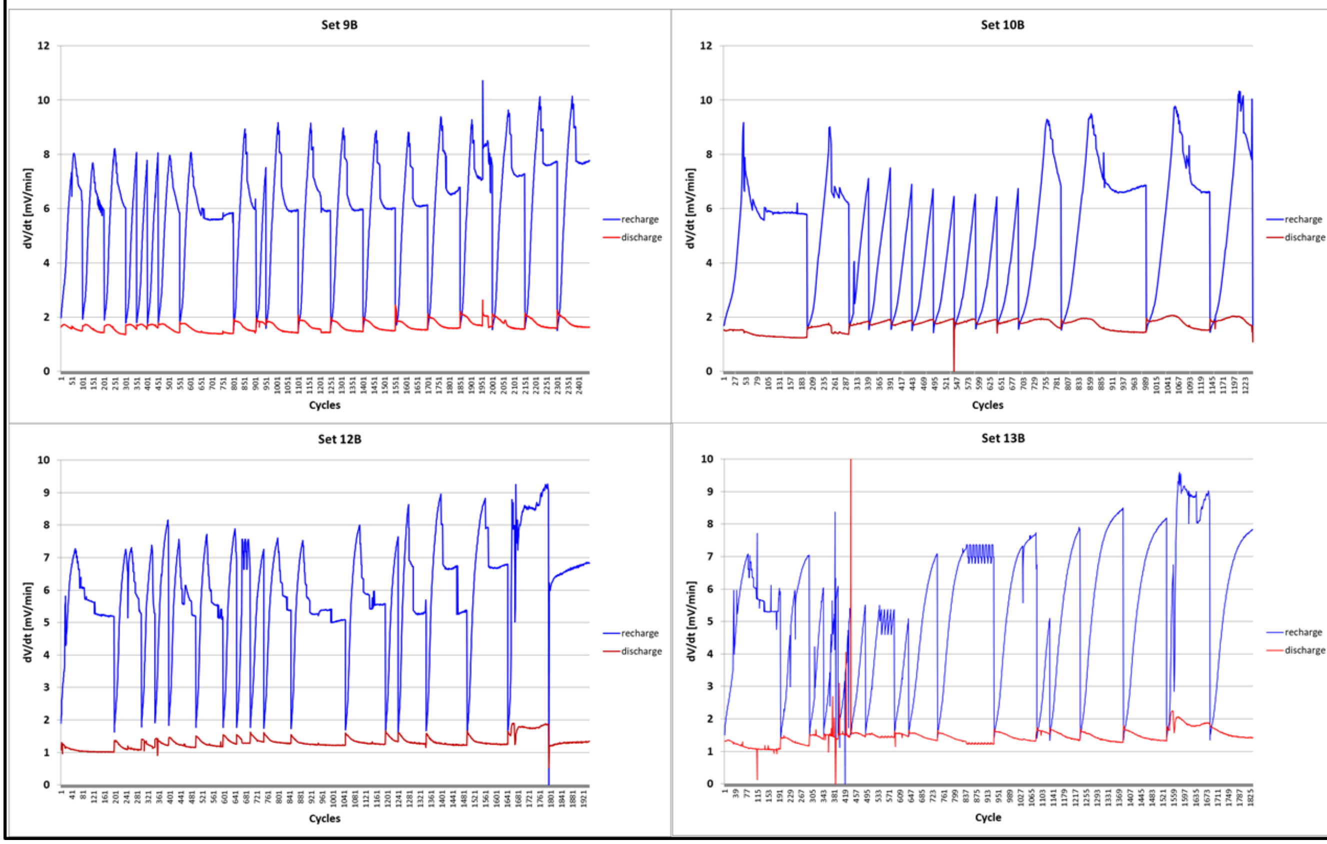
For all cases, dV/dt is not a continuous line. Rather, it presents notches, where dV/dt drops to very low values. This happens when the battery is submitted to capacity tests done from time to time. During capacity tests, the battery goes from full charge to full discharge state, and vice-versa, and this process tends to equalize internal electrical charges, which makes the battery's dV/dt behave as if it were new, for a while. The dV/dt measured just after a capacity test is very low (as shown in the graphics), but soon recovers to its actual value.

Even considering all of these interfering factors, it is possible to see that dV/dt rises when the battery is reaching its EoL. A better way to avoid misinterpretation is to average daily values of dV/dt over several days – for instance, 5 continuous days. By so doing, the resulting curve is smoother, and makes a decision easier. The EoL indication is given when the averaged dV/dt reaches a given threshold.

For our purposes, it is important to get an alerting signal when EoL is approaching, not when it is actually reached. For sets 9B and 10B, which were aged at 40ºC, that happened at the 10mV/min level. For sets 12B and 13B, aged at 50ºC, the threshold should be at 9mV/min. Both reference the recharging phase. For the discharging phase, obtained data is less consistent, even using a constant current sink as a load.

For field application, the EoL estimation through dV/dt method is very simple: voltage and current can be achieved through cheap sensors connected to every battery in the PV power plant. The data processing is also simple and can be done with a low-cost processor board. The processed dV/dt is then sent to a monitoring system, located at the energy utility's office, on a daily basis.

Figure 3. Results from dV/dt algorithm



Battery Monitoring System with the EoL Algorithm

The developed algorithm was embedded in a Battery Monitoring System. This system consists of the following hardware:

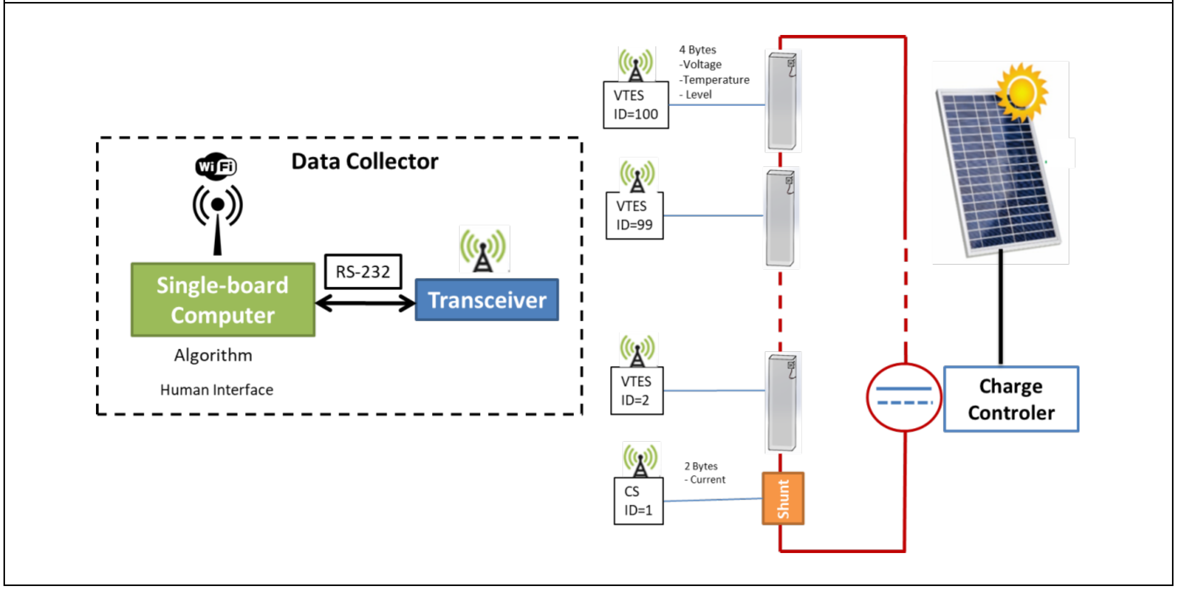
- Voltage, Temperature and Electrolyte Level Sensor (VTES): installed on the battery container and is responsible for the measurements of voltage and temperature, and indicates if the electrolyte level is below the minimum threshold. Each cell from the battery bank has one VTES.

- Current Sensor (CS): installed on a shunt resistor and it is responsible to measure the current from the battery bank.

- Data Collector (DC): it is composed of a transceiver and single-board computer. The transceiver communicates via radio with the sensor to collect the measurements and send them to the computer via RS-232 communication. The single-board computer is responsible to store the data, run the dV/dt algorithm and present all the information in a human-interface.

Figure 4 illustrates a preliminary schematic of the Battery Monitoring System. It is important to note that all the sensors installed on the battery bank use wireless communication, avoiding a lot of cables in the battery environment.

Figure 4. Schematic of the Battery Monitoring System with the EoL Algorithm Embedded



The battery monitoring system developed, with all sensors and hardware, was tested in the laboratory to validate the collected data. The algorithm and the monitoring system were tested in an off-grid PV system in order to produce the highest fidelity, the real harsh operating condition of the battery. Figure 5 shows the components of the hardware, namely: the VTES connected to the battery container, the CS on the battery container and connected to the shunt resistor and the DC that has a single-board computer with the algorithm embedded.

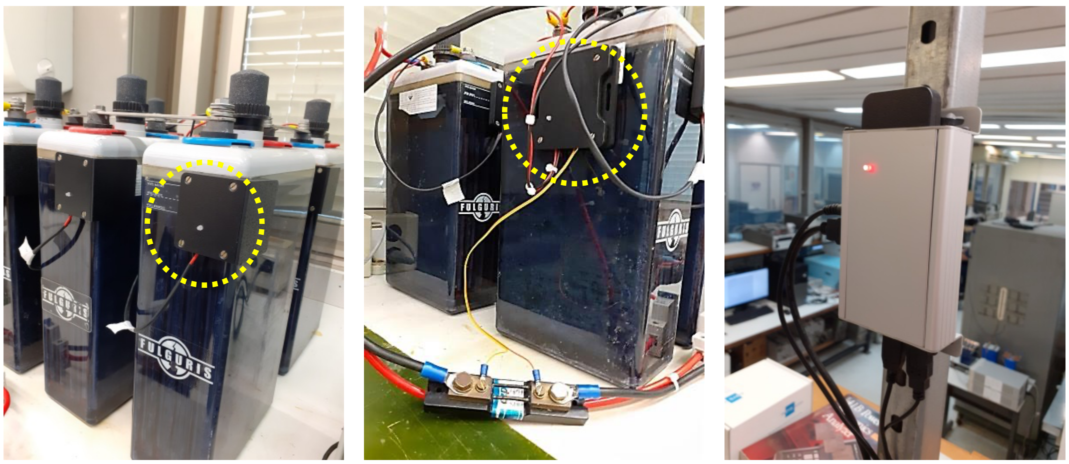


Figure 5. VTES connected to the battery, CS with shunt and the DC with the computer inside, respectively

For the validation of the algorithms in the PV system, different test scenarios were created with the battery bank: (i) only healthy batteries (SoH above 95%), (ii) one battery that reached EoL and the others healthy, and (iii) a healthy battery and the others degraded. The EoL algorithm detected the degraded battery in all the scenarios.

One aspect to be considered is that the dV/dt algorithm has an initial transient period to work correctly. The minimum period is 21 days, which includes the initial date (whose data are usually discarded because it contains transients), 15 days of useful measures, and 5 days of post-processing (false positive filter).

Conclusion

Obtained results show that it is possible to predict when a battery will achieve its EoL by monitoring only voltage and current, and using simple algorithms, suited for a low complexity processor. The paper presented the developed algorithm, which is a modified version of rate of voltage change (dV/dt), making use of the relationship between electrical charge and voltage level to identify the EoL proximity of the battery. Ongoing work aims to include temperature data in order to allow a better result.

The dV/dt becomes more accentuated as the battery ages, making it possible to identify the thresholds reached at the battery's EoL with the data collected in the laboratory. The resulting system is simple, composed of a set of low cost sensors and it doesn't need any special infrastructure. It is non-invasive, since needed data can be gathered with the battery in normal operating mode. It is robust, giving EoL indication for different battery sets, which indicate ageing history due to different operating conditions.

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