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New battery model considering thermal transport and partial charge stationary effects in photovoltaic off-grid applications

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HIGHLIGHTS

- We detect the need to model certain underrated effects in PV ESS sites.
- We propose a new battery model that incorporates these processes.
- We design the laboratory tests required to feed the model.
- Outcomes are compared to data from both real installations and laboratory.

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ABSTRACT

The optimization of the battery pack in an off-grid Photovoltaic application must consider the minimum sizing that assures the availability of the system under the worst environmental conditions. Thus, it is necessary to predict the evolution of the state of charge of the battery under incomplete daily charging and discharging processes and fluctuating temperatures over day-night cycles.

Much of previous development work has been carried out in order to model the short term evolution of battery variables. Many works focus on the on-line parameter estimation of available charge, using standard or advanced estimators, but they are not focused on the development of a model with predictive capabilities. Moreover, normally stable environmental conditions and standard charge-discharge patterns are considered. As the actual cycle-patterns differ from the manufacturer's tests, batteries fail to perform as expected.

This paper proposes a novel methodology to model these issues, with predictive capabilities to estimate the remaining charge in a battery after several solar cycles. A new non-linear state space model is proposed as a basis, and the methodology to feed and train the model is introduced. The new methodology is validated using experimental data, providing only 5% of error at higher temperatures than the nominal one.

1. Introduction

Small scale generation systems that use renewable sources are becoming popular in some specific applications, and almost all of them require the use of energy storage systems, usually battery packs. On the one hand battery packs are used to store energy and power the application during non-generation periods like, for example, night-time in Photovoltaic (PV) applications. On the other hand, the other main purpose when including batteries in small-scale generation systems is to mitigate the unforeseeable energy production rates that most renewable sources offer, such as cloudy or misty weather (PV application) or non-windy periods (wind application). In off-grid systems, these technologies are mainly based on electrochemical storage through batteries, using well-known chemistries such as Valve Regulated Lead-Acid (VRLA) batteries [1] and usually with stationary features.

When it comes to designing one of these Energy Storage Systems (ESS), engineers usually consider battery manufacturer's datasheets as their main tool for battery sizing purposes. Manufactures use laboratory experiments to characterize their batteries but in very specific conditions, e. g. fixed optimum test temperature, full-charge tests, etc. These controlled tests do not usually fit the real performance conditions of renewable energy applications (because of the unstable conditions

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concerning off-grid installations) and so, the results cannot be extrapolated. Moreover, in off-grid system applications these uncontrolled parameters have a huge impact on battery performance [2]. As there is almost no information about the influence of these variations, from manufacturer's tests to real applications, electrical engineers are forced to oversize the installation designs, as a measure to avoid energy supply disruption.

This study addresses how to model some of these uncontrolled effects in batteries related to off-grid PV sites. The main environmental variables that have an influence on this kind of installation are temperature and insolation. On the one hand, while temperature impact is measured by battery manufacturers over many cycles [3], temperature variations within the same cycle are not studied. On the other hand, regarding insolation, uncertainty exists regarding over time incomplete charge cycles, and the decrease in effective battery capacity that they produce. As a previous work to this paper, these issues have been described in Ref. [4], and are not usually modeled together.

Nowadays, there is an increasing interest in the research of battery models (mainly boosted by their use in the Electric Vehicle application (EV) and on-grid ESS). These technologies are mainly specialized in cycling capabilities, such as batteries based on Lithium-Ion or ultracapacitors [5-7]. This fact has caused an increase in battery modelling effort in literature, but unfortunately, simulation of off-grid PV ESS applications is not the main aim of these studies. The modelling techniques that have been proposed can be mainly classified into on-line estimation algorithms [8] or off-line simulation models [9], and are mainly focused in diagnosing performance parameters throughout the battery use, such as estimating State-Of-Charge (SOC) [10,11], or service life (State-Of-Health, SOH) [12,13].

Moreover, most studies are usually addressed in nominal temperature conditions (20 °C or 25 °C) where batteries perform best, omitting the huge impact that temperature has on features like capacity or degradation. If considered, temperature is mostly addressed as a static variable, omitting temperature changes within the same cycle [14,15]. Hence there is also uncertainty regarding the impact of charge–discharge cycles in non-constant temperature environment [4]. Being deployed in remote, isolated locations, off-grid PV ESS applications are greatly affected by this specific kind of thermal cycles, which have an important impact on charge estimators and energy management policies.

Additionally, in off-grid PV applications battery packs suffer from incomplete charge cycles. When testing a battery in a laboratory, manufacturers use complete charge processes to measure the battery capacity. During these tests, batteries are kept in float stage for several hours, typically 72 h [3,16,17], and can be considered fully charged prior to the test. Once discharged, all the energy is drawn from them. However, in a real ESS with one battery pack in an off-grid PV application, batteries cannot remain in that stage so many hours, since batteries are discharged during the night. This incomplete charge processes leads to a steady partial charge state, as described in Ref. [4] that lowers the effective available charge for non-generation periods.

Coming ESS generations will include more than one energy storage packs, and there will be an increasing number of publications related to energy management policies, which control the power flow inside the ESS. In order to simulate these behaviors and to develop new intelligent policies, a well fitted battery simulation model will be needed.

This paper proposes a new battery model intended for off-grid PV applications, which is able to make long-term predictions, and not only short-term estimations based on past or real-time data. The model introduces a novel thermal transport estimation feature that considers charge and discharge processes at different temperatures within the same cycle. It is also capable of performing accurate estimations of the remaining charge inside a battery after several incomplete charge cycles with progressive temperature changes. The model performs long term predictions and performance simulations of ESS, being able to forecast SOC in off-grid PV applications with real world conditions In this paper, SOH is not taken into account, since it is not possible to evaluate its impact on battery performance in the short term, and its effects can be ignored in a short time window. Future work will deal with this issue, leading to a more complex model.

2. Methodology

Typically, batteries work in the Current Regulation Phase (the charger fixes the current through the battery) while charging. As the battery charges it voltage rises, until it reaches a value established as the float voltage. When this happens, the battery charger switches to Voltage Regulation Phase and the current that the battery draws decreases over time (current tail). Furthermore, in this application (off-grid supplied telecom equipment), the load demands a constant current from the battery. This will be relevant when choosing inputs or outputs to the model.

2.1. Model description

The aim of the battery model is to: a) replicate the battery charge over time, and b) provide the related voltage. When dealing with charge, the most widely used parameter is *SOC*. Many studies have addressed *SOC* estimation using different approaches [13]. Extended Kalman Filter (EKF) together with circuital modelling [18] is one of the most popular, intended for on-line estimation applications. Coulomb Counting (CC) is another approach [19] similar to State-Space (SS) modelling. The latter is the modelling approach retained in this paper.

2.1.1. Basic battery model

Before proceeding, some definitions are required:

- Q: represents the stored charge in the battery. This charge is obtained with the CC or SS method, by integrating the input current through the battery terminals.
- C_{NOM}: is the rated capacity of the battery, as specified by the manufacturer. Usually measured at 20 °C or 25 °C, and in full charge conditions.
- i_{batt}: represents the current that flows through the battery terminals.
- SOC: is the traditional definition of State-Of-Charge, obtained by comparing the stored charge Q with the rated capacity C_{NOM} as displayed in (1). The definition in (2) can be obtained applying the CC method. An alternative definition (SOC_V) will be used, as explained further [11].

$$SOC \triangleq \frac{Q}{C_{NOM}} \times 100\%;\ SOC \in [0,100] \tag{1}$$

$$SOC(t) = \frac{1}{C_{NOM}} \int_{-\infty}^{t} i_{batt}(\tau) d\tau \tag{2}$$

- OCV: is the Open Circuit Voltage of the battery, i.e. its voltage with no current flow through its terminals and once the relaxation of the battery is completed. It is related to the SOC by a non-linear relationship.
- v_{batt}: represents the voltage measured at the battery terminals, with or without current. OCV and v_{batt} are related by the battery output impedance model and i_{batt}.

A first hypothesis is made to formulate the model: Q is supposedly predictable, that is, considering the evolution of external variables of the system (current patterns, float voltage and temperature) it is possible to compute the evolution of Q. An internal description through a SS model has been retained where the SOC, defined as in (1), represents a tentative State Variable, see Fig. 1a. The basic model estimates SOC through the well-known method of CC (2). Input current integration is translated into the remaining charge inside the battery, which acts as a