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A novel lifetime prediction method for lithium-ion batteries in the case of stand-alone renewable energy systems

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ABSTRACT

This paper presents a mathematical formulation of lithium-ion batteries, including aging and temperature effects. The model is developed by integrating the simplified single particle model (SSPM) and reduced-order model (ROM) to predict solid electrolyte interphase growth (SEI). Results show agreement with the experimental data at 25 °C operating temperature and moderate cycling currents. A maximum error of 3.6% in finding the battery discharged Ah is observed in harsh operating conditions, including 60 °C and approaching the end of life of the battery. Due to the typical operating conditions of stand-alone renewable energy systems, more accurate estimations are expected. Finally, this methodology is utilized to predict the lifetime of lithium-ion batteries that are combined with PV generators to supply electricity to an isolated house situated near Zaragoza, Spain, under two control strategies. The results indicate realistic lifetime predictions when using the model in real operating conditions for this kind of system. Besides, by maintaining the batteries in states of charge of lower than 70%, around 55% increase in the battery lifetime can be achieved at the cost of 0.23% reduction in the percentage of the electrical load that is able to be covered by the stand-alone system.

1. Introduction

The spread of using renewable energy systems in the electricity sector will play a catalyzing role in modernizing the electricity grid [1]. By increasing the utilization of intermittent renewable energy resources, a greater emphasis on storage technologies to compensate for the energy mismatch between demand and supply, especially in off-grid systems, would be evident [1–5]. Although nowadays lead-acid batteries are the prevailing technology for storing excess electricity in stand-alone renewable energy systems [2,5–9], lithium-ion batteries are expected to be dominant in the near future due to their longevity and decreasing unit price [1,10–14]. Diouf et al. [15] called lithium-ion batteries the first-choice battery to store energy, and they mentioned this kind of battery as being the ultimate energy storage technology in renewable-based installations. Although these authors presented the electric vehicle sector as the driving force for this goal, it seems that utilizing lithium-ion batteries in renewable energy systems in a parallel market can also be taken into account, since costs will further fall as production volumes increase. Prior to any installations, design and operation optimization is essential, specifically for finding the most economic combination of the system configuration and control strategies to meet the required load.

Since battery lifetime prediction is crucial in optimization frameworks, in this research we will focus on specific features of lithium-ion batteries aging in the case of stand-alone renewable energy systems. To this aim, the paper is outlined as follows: First, in Section 2, the state-of-the-art battery lifetime prediction methods are discussed in details and the main contribution of this work is highlighted. In Section 3, we will describe the general mathematical formulation of the proposed method. In Section 4, the solution strategy will be explained. The model will be validated in Section 5 using experimental data which has been reported in the literature. Afterward, the results of implementing the model to a case study will be discussed. Last, the paper will be concluded in Section 6.

2. State-of-the-art battery lifetime prediction methods

Dufo-Lopez et al. [16] compared the different lead-acid lifetime prediction models to be used in stand-alone renewable energy systems. They concluded that estimating the real lifetime of batteries, which is a function of system operating conditions, is an important task. A deviation from the accurate longevity of the battery will lead to a greater error in calculating system's levelized cost of electricity and optimization results. This importance has also been highlighted in Refs. [17,18].

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Nomenclature

a_s, $m^2\,m^{-3}$	active surface area per electrode unit volume, $a_s = \frac{3\varepsilon_s}{R_s}$,
A	electrode plate area, m^2
c	concentration of Li in a phase, $mol\,m^{-3}$
c^s	surface concentration of lithium in the solid phase, $mol\,m^{-3}$
E_a	activation energy, $J\,mol^{-1}$
F	Faraday's constant, 96,487 $C\,mol^{-1}$
I	discharge current, A (I > 0 discharge; I < 0 charge)
i_0	exchange current density, $A\,m^{-2}$
j^l	volumetric intercalation current density, $A\,m^{-3}$
j^{Li}	total volumetric current density, $A\,m^{-3}$
l_s	diffusion length $l_s = R_s/5$ for spherical particles, m
M	molecular weight, $kg\,mol^{-1}$
Q	capacity (A h)
R	universal gas constant, 8.314 $J\,mol^{-1}\,K^{-1}$
R_c	contact resistance, $\Omega\,m^2$
R_f	film resistance, $\Omega\,m^2$
R_s	radius of active material particles, m
SOC	state of charge
T	absolute temperature, K
T_{ref}	reference temperature, 298 K
t	time, hours
U	open circuit or equilibrium potential, V
V	voltage, V
x	negative electrode solid-phase stoichiometry (anode lithiation state)
y	positive electrode solid-phase stoichiometry (cathode lithiation state)
z	spatial coordinate, m

Greek symbols

α	transfer coefficient for an electrode reaction
δ	thickness, m
Δt	time interval, hours
τ	time, s
ε	volume fraction or porosity of a phase
η	overpotential of an electrode reaction, V
κ	conductivity, $S\,m^{-1}$
ρ	density, $kg\,m^{-3}$
ϕ	phase potential, V
ψ	transport parameters

Subscript

e	electrolyte phase
f	film
filler	filler
max	maximum value
n	negative electrode
p	positive electrode
r	region (negative electrode (n), separator (sep) or positive electrode (p))
s	solid phase
s/e	solid/electrolyte
SEI	solid electrolyte interphase
sep	separator
0%	corresponds to fully discharged battery
100%	corresponds to fully charged battery

Superscript

avg	average
eff	effective
Li	lithium species
ref	reference condition
s	side reaction
0	initial value

However, aside from the immense importance of battery life prediction, aging estimation is very complicated due to the various kind of mechanisms and governing equations [19–21]. Although these conclusions were taken from lead-acid-based renewable energy systems, the same deductions can be expected in the case of lithium-ion batteries in which battery unit price is even higher and the need for system optimization is obvious. Uddin et al. [22] have recently illustrated how considering a battery degradation model of lithium-ion batteries in renewable energy systems can alter economic feasibility of the project.

Although lifetime optimization is a time-consuming task by its nature, it is necessary to find the most economic combination of components' sizes and control strategies of stand-alone renewable energy systems. Furthermore, adding more complexity to battery models to take aging phenomena into account will increase model runtime significantly. To solve this problem, efficient battery lifetime prediction methodologies should be developed in a conservative way to keep the model both simple and accurate.

Lots of mechanisms participate in degradation of Li-ion batteries. These phenomena can occur in cell anode, electrolyte and separator, cathode and even in exterior cell components [23,24]. However, all the aging causes are not of the same importance and depend strongly on battery chemistry and operating conditions [25].

Among the different aging mechanisms that is probable to happen in a Li-ion cell, formation of the SEI layer at the anode electrode/electrolyte interface is one of the most principal mechanisms that is either studied or quantified [25–31].

Barre et al. [32] reviewed Li-ion battery aging mechanisms and estimation procedures. These methods include electrochemical models [33], equivalent circuit models [34], performance models [35] and analytical and statistical approaches [36–38]. After describing the pros and cons of them, the authors mentioned that model accuracy and runtime are key factors for developing new methodologies.

Dufo-Lopez et al. [6] compared three different aging models to predict Li-ion battery lifetimes in stand-alone renewable and hybrid renewable energy systems. They mentioned that sometimes simplified correlations that have been extracted by accelerated aging tests may lead to optimistic lifetime predictions, as in case of Wang et al.'s [39] model, in which a detailed look at the operating conditions of the system has not been considered. On the other hand, in some cases, simple, empirical cycle-life relations, such as Groot et al.'s [40] model, may result in better estimations for hybrid systems in which battery size is smaller and, as a result, operating current is higher. However, as emphasized by Smith et al. [41], high-rate cycling may not end in realistic predictions in the case of low operating rate applications (as in stand-alone PV-only renewable energy systems with higher days of autonomy for the battery bank) due to the more available time for the side reactions to proceed.

The physico-chemical phenomena that occur during battery utilization and the impact of cell engineering design on battery performance can be studied through electrochemical based modeling approaches [42]. However, adding complicated governing equations to estimate battery lifetime with an intricate electrochemical model will intensify model complexity. To overcome this difficulty, researchers have tried to develop reduced-order battery aging models by considering some