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Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model

Arpit Maheshwari[a,b], Nikolaos G. Paterakis[a,*], Massimo Santarelli[b], Madeleine Gibescu[c]

[a] Department of Electrical Engineering, Eindhoven University of Technology, 5600MB Eindhoven, the Netherlands
[b] Politecnico di Torino, Corso Duca Degli Abruzzi 24, 10129 Turin, Italy
[c] Copernicus Institute of Sustainable Development, Utrecht University, 3584CB Utrecht, the Netherlands

HIGHLIGHTS

- A degradation-aware market participation model for stationary storage is proposed.
- A non-linear degradation model is built from experimental data for Li-ion batteries.
- The non-linear degradation model is compatible with a MILP formulation.
- A decomposition technique for solving efficiently long-horizon problems is proposed.
- The proposed model is benchmarked against commonly used degradation models.

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ABSTRACT

Given their technological and market maturity, lithium-ion batteries are increasingly being considered and used in grid applications to provide a host of services such as frequency regulation, peak shaving, etc. Charging and discharging these batteries causes degradation in their performance. Lack of data on degradation processes combined with requirement of fast computation have led to over-simplified models of battery degradation. In this work, the recent experimental evidence that demonstrates that degradation in lithium-ion batteries is non-linearly dependent on the operating conditions is incorporated. Experimental aging data of a commercial battery have been used to develop a scheduling model applicable to the time constraints of a market model. A decomposition technique that enables the developed model to give near-optimal results for longer time horizons is also proposed.

1. Introduction

Lithium-ion battery technology has increased in popularity in recent years driven by its demand in electric vehicles [1,2]. The combination of performance, flexibility and decreasing costs has also made it attractive for integration in power systems. Numerous studies shed light upon scheduling strategies for battery-based storage in providing grid services. However, lithium-ion batteries have a limited life [3–5]. With time and use degradation processes occur, leading to a loss in capacity (capacity fade) and a loss in power capability (power fade). Thus, accurate determination of degradation is imperative in such models, not only in order to be realistic in determining the business case, but also to develop intelligent strategies for charge–discharge scheduling of these batteries.

1.1. Literature review

Several market studies on batteries focus on the economic viability of the storage options from a long-term perspective, while others focus on optimizing their short-term operational strategy. The modus operandi of such studies is to develop a model that jointly simulates the market and battery behaviour. Modelling of the market mechanisms has been comprehensive, with studies considering a single [6,7], multiple [8,9] or a combination of markets [10–12], assuming perfect price information [8,9,13,14] or uncertainty in prices [12,15].

Battery models in power system and market studies often completely ignore degradation [13,15,16]. In some works, degradation is calculated post-optimization. As a result, the operation strategy is short-sighted and does not consider the battery as a time-limited and costly resource [17–20].

* Corresponding author.
E-mail address: n.paterakis@tue.nl (N.G. Paterakis).

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Nomenclature

Parameters

- l parameter representing the horizontal change between two consecutive points defining the piecewise linear function δ^{1C}
- m parameter representing the vertical change between two consecutive points defining the piecewise linear function δ^{1C}
- n total number of segments of a piecewise linear function
- s parameter representing SOC values of points defining the piecewise linear function δ^{1C}
- I_{1C} 1C current (A)
- $P_t^{ch,max}$ maximum power input to the battery in the trading interval t (W)
- $P_t^{dis,max}$ maximum power output from the battery in the trading interval t (W)
- Q rated capacity of the battery (Ah)
- V_{nom} nominal battery voltage (V)
- $\delta^{1C}(s)$ parameter representing y coordinates of points defining the piecewise linear function δ^{1C}
- η efficiency of the storage system
- λ_t market clearing price for the trading interval t (€/ Wh)
- ω weighting factor
- ΔT duration of a trading interval (h)

Decision Variables

- d_t degradation during the trading interval t (Ah)
- d_t^{1C} degradation at 1C current rate for the change in battery state during the trading interval t (Ah)
- i_t current rate during the trading interval t (h^{-1})
- u_t binary variable. 1 when storage system is charging in trading interval . else 0
- $v_{t,i}$ modelling variable introduced to implement incremental cost formulation
- $z_{t,i}$ binary variable introduced to implement incremental cost formulation
- D total degradation in the market period (Ah)
- $P_t^{ch,b}$ power input to the battery in the trading interval t (W)
- $P_t^{ch,m}$ power input from the market in the trading interval t (W)
- $P_t^{dis,b}$ power output from the battery in the trading interval t (W)
- $P_t^{dis,m}$ power output to the market in the trading interval t (W)
- R revenue (€)
- SOC state of charge, measure of the remaining capacity of the battery, defined as the ratio of the current capacity to the total capacity, expressed in percent
- δ_t^{1C} cumulative degradation function value computed for 1C at the end of trading interval t
- ζ composite objective function value
- ψ degradation scaling factor to account for current dependence

Indices

- i index of points defining the piecewise linear function
- t trading interval index

Terms

- DOD depth of discharge or cycle depth, defined as one half of the fraction of full cell capacity used during one cycle, expressed in percent
- EFC equivalent full cycle, a measure of charge throughput equal to two times the capacity of a new battery
- SOC_t state of charge of the storage system at the end of trading interval t

Degradation-aware battery scheduling studies use either a constraint-based approach [11,21,12] or an objective-based approach [9,22,23]. In [10], the constraint-based approach has even been combined with the objective-based approach. In the constraint-based approach, to extend the life of the battery, one or more of the following variables are constrained: power, number of cycles per day, depth of discharge (DOD), maximum and minimum state of charge (SOC). Such approaches that do not model the degradation behaviour at all return non-optimal results.

In the objective-based approach, the cost of battery degradation is included as an economic cost in the objective function. Traditionally two main methods to model degradation have been used: the Ah throughput method [23,24] and the method of cycle life vs. DOD power function [9,11,22]. In the first method, it is assumed that a certain amount of energy can be cycled through a battery before its end of life, irrespective of the depth of discharge. In the second method it is assumed that the number of cycles that a battery can perform is inversely proportional to the amplitude of DOD given by a simple power function. The origins of the two most employed methods for quantifying degradation, cycle life vs. DOD and Ah throughput, can be traced to modelling the lead-acid battery degradation behaviour [25–27].

From the point of view of objective function, most approaches are single objective, where degradation is assigned an economic cost. This cost is often based on the battery replacement cost [9,18,28,29], sometimes on the economic utilization costs (investment & operating) [30] and other times on the marginal cost of operation [31]. The above discussion has been summarized in Fig. 1.

1.2. Gaps in modelling degradation phenomena in lithium-ion batteries

While the modelling of the market part of the scheduling models has been comprehensive, modelling of battery degradation phenomena is

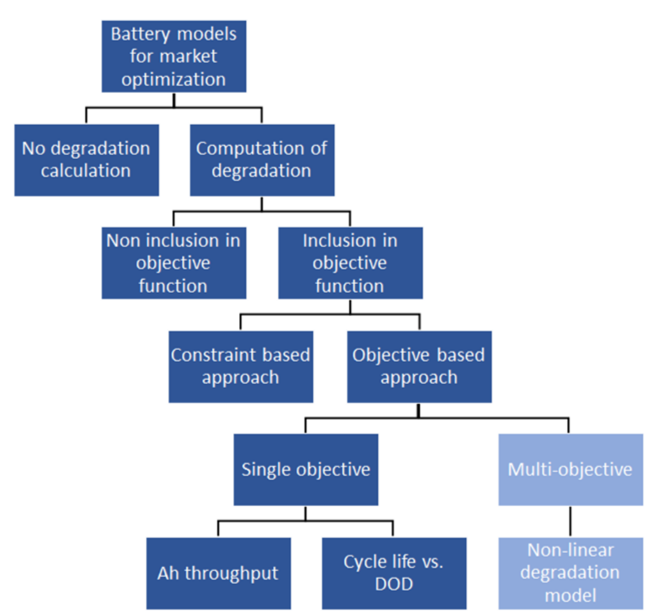

Fig. 1. Summary of battery models used for market studies (the contribution of this work highlighted using a lighter shade).