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Optimal operation of a battery energy storage system: Trade-off between grid economics and storage health

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ABSTRACT

The utilization of grid-scale energy storage is growing exponentially due its decreasing costs and added flexibility to providing numerous services. Among the currently available storage systems, batteries based on lithium-ion chemistries are poised to provide a significant share of such flexibility due to their high power and energy density, and relatively low cost per unit energy. However, research on such systems has been segregated into focus on its chemical properties, and focus on the grid integration separately. This paper proposes a data-driven framework to characterize battery energy storage systems embedded into a decision-making optimization model. The model embeds two mechanisms, variable C-rates and variable efficiencies, so that batteries may be scheduled at high-power (high C-rate) operations to capture additional grid revenues, only if economical against the cost of degradation effects. The framework is applied to stationary battery energy storage systems in retail markets in order to explore the improved energy arbitrage benefits.

1. Introduction

The utilization of grid-scale battery energy storage systems (BESS) is growing exponentially with 340 MW of installed capacity in 2013, and a projected capacity of over 40 GW by 2022 [1]. Such rapid growth is due to BESS's flexibility in providing numerous grid services including energy arbitrage, frequency regulation, transmission deferral and reactive power support, among others. Of the various types of storage technologies, BESS based on lithium-ion (Li-ion) chemistries are poised to provide a significant share of such flexibility due to their high power and energy density and relatively low cost per unit of energy.

Research on BESS has typically been segregated into two main centers of interest: (i) focus on the chemistry and material properties, *e.g.* [2–6], and (ii) focus on the grid integration, operation, and economic performance, *e.g.* [7]. This gap is notorious in both the research community and in commercial usage of batteries; especially for grid applications where the market-based decision-making tools use simplified models that thwart the full operating flexibility of the battery because cycle-life degradation and charging/discharging efficiencies are not properly characterized. This discrepancy is caused by the development of the typical highly non-linear empirical or theoretical degradation models, *e.g.* [2–6,8–16], which introduce a computational burden when optimizing over a multi-period time horizon. The complexity of typical models stem from predicting the physicochemical cause of degradation – active material loss, loss of lithium inventory, mechanical stress, SEI layer growth, among others. While useful for understanding the failure mechanism and predicting the remaining capacity or lifetime of a battery, such detail makes it difficult to extend the models to various chemistries and/or use cases. Furthermore, the added mechanistic information does not necessarily aid in the high level optimal decision-making strategy for power grid participation. By combining the economic exploitation of BESS for grid services with a simple, yet descriptive data-driven characterization of key internal chemical properties, the decision-making processes are improved.

Some pioneering works exist on bridging the gap between battery degradation mechanisms (*e.g.*, growth of resistive surface films, degradative side reactions, lithium loss, among others) and grid economics [17–23]. In [17], BESS is explored in the context

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Nomenclature

α_t^{ES+}	charging power loss in period t
α_t^{ES-}	discharging power loss in period t
Δt	time interval
$\ell_{t,i}$	C-rate in each block i in period t
$\mathcal{I}$	set of piece-wise blocks with index i
$\mathcal{T}$	set of time periods with index t
$\bar{L}_i$	max. pre-defined C-rates in each block i
$\bar{P}^{ES}$	maximum power rating
$\bar{SoC}^{ES}$	max. state-of-charge
τ_t	electricity prices in period t
$\underline{SoC}^{ES}$	min. state-of-charge
a^+	second-degree polynomial coefficient for charging
a^-	second-degree polynomial coefficient for discharging
b_t	state-of-health loss in period t
BC^{ES}	BESS rated capacity
C^{ES}	BESS price
eta^+	fixed charging efficiency
eta^-	fixed discharging efficiency
k_i	degradation slope ($\%/cycle$) in block i
p_t^{ES+}	charging power of BESS in period t
p_t^{ES-}	discharging power of BESS in period t
soc_t^{ES+}	charging energy in period t
soc_t^{ES+}	discharging energy in period t
$SoC_{t=0}^{ES}$	initial state-of-charge
soc_t^{ES}	energy state-of-charge in period t
x_t	auxiliary binary variable in period t

of a microgrid considering both cycle-life degradation and power losses due to the charging/discharging. However, the battery model is assumed to charge up to only ±1C rates (*i.e.* charge or discharge the full capacity in 1 h), which reduces grid revenues that could be obtained from variable C-rate operations. Also, cycle-life degradation and its cost is assumed constant regardless of the battery chemistry, which simplifies the true effect of degradation. In [18], an empirical cost function based on battery degradation as a function of depth-of-discharge (DOD) was incorporated into the model predictive control of a peak shaving algorithm; however, the degradation dependence on charging rates are also ignored. An optimization model was developed in [19] to operate BESS with stochastic wind resources, while considering degradation. To ensure the BESS lasts an expected lifetime in years, a maximum daily degradation percentage was preset in [19], even though there may be cases where it is lucrative to discharge the BESS while considering the increased degradation. Such an approach results in sub-optimal economic performance. In other works, the trade-off between charge optimization and battery degradation is explored in [20–23] for electric vehicle (EV) Li-ion batteries. In [20], empirical degradation models specific to a single Li-ion chemistry are implemented, as opposed to a data-driven approach that can be applied to any chemistry. In [22,23], detailed models are developed to perform the economic tradeoff between EV charge management and degradation. However, variable C-rate operation was not considered and the models are highly non-linear.

The work in this paper proposes a data-driven method to characterize BESS embedded into a decision-making optimization model. Such data-driven approaches enable the major battery characteristics along with grid economics to be co-optimized. The mathematical model is formulated as a mixed integer linear program (MILP), which benefits from low computational burden. As for characteristics, the BESS undergoes cycle-life degradation as a function of its operation in terms of C-rate charging/discharging, *i.e.* amount of energy that is charged/discharged in a certain timestep. Additionally, the internal resistance of the BESS leads to charging/discharging power losses which are also functions of the battery operation. These two mechanisms, variable C-rates and variable efficiencies, are embedded into the model so that batteries may be scheduled at high-power (high C-rate) operations to capture additional grid revenues, only if economical against the cost of adverse effects on the BESS.

The main contributions of this work are:

- A complete MILP model for BESS considering the effect on cycle-life degradation and variable efficiency based on its operations.
- A data-driven method to transform variable C-rate degradation and efficiencies into economic proxies that can be included into the optimization framework.
- Application of a BESS exploiting energy arbitrage under local retail electricity tariffs while considering tradeoff between potential revenue and degradation.

The remainder of this paper is organized as follows. Section 2 describes the approach for characterizing Li-ion batteries for grid operations. Section 3 develops the optimization model for BESS and Section 4 shares the results. Finally, Section 5 concludes the paper.

2. Data analytics of Li-ion batteries

Lithium ion batteries are popular energy storage technologies due to their high energy density and Coulombic efficiency. However, the capacity of these chemistries fades over time due to degradative processes occurring alongside the main electrochemical reactions [24]. This capacity fade determines the usable lifetime of the batteries and is a function of how that battery is operated. In addition to the long-term capacity fade of these batteries, the internal (ohmic) resistance of the cells leads to power losses during charging/discharging. These losses affect the Coulombic efficiency of the battery and are also a function of the battery's operation [25]. To improve the accuracy of the optimization of this BESS, the effects of battery operation on the cycle-life and efficiency are considered.

Fig. 1 shows the three-step flow chart, which includes (1) experimental testing, (2) data analysis, and (3) system optimization. Two experiments are performed during the experimental testing phase, which are cycle-life testing to characterize the impact of variable C-rate charging on the BESS, and current measurements to characterize variable efficiencies. In the next step after the experiments are complete, data analysis takes place to derive mathematical functions that best represent the experimental data for variable C-rate and efficiency mechanisms. Lastly, these functions are directly embedded into the BESS optimization to perform the trade-off between grid revenues, and battery degradation and power losses. The next subsections explain in detail the steps presented in Fig. 1.

2.1. Variable C-rate degradation mechanism

Lithium-ion batteries undergo cycle-life degradation as a function of increased C-rates [5]. C-rate is defined as the charging/discharging current normalized by the current which would charge/discharge the nominal capacity of the battery in an hour, *e.g.* +1C and +3C are equivalent to charging the battery in 1 h and 20 min, respectively.

In order to obtain representative cycle-life characteristics, Li-ion nickel-manganese-cobalt (Li-NMC) batteries, specifically 1.5 A-hr Samsung INR18650 cells [26], were cycled continuously at specified C-rates using a Maccor 4300M battery cycler [27]. In this context, a cycle is defined as a full constant current constant voltage (CC-CV)