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Impact of battery degradation on energy arbitrage revenue of grid-level energy storage

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ABSTRACT

This study investigates the representation of battery degradation in grid level energy storage applications. In particular, we focus on energy arbitrage, as this is a potential future large-scale application of energy storage and there is limited existing research combining the modelling of battery degradation and energy storage arbitrage. We implement two different representations of battery degradation within an energy arbitrage model, and show that degradation has a strong impact on battery energy storage system (BESS) profitability. In a case study using historical electricity market prices from the MISO electricity market in the United States, we find that the achievable net present value (at an interest rate of 10%) for a battery system with a C-rate of 1C dropped from 358 $/kWh in the case considering no degradation to 194–314 $/kWh depending on the battery degradation model and assumptions for end of life (EOL) criteria. This corresponds to a reduction in revenue due to degradation in the 12–46% range. Moreover, we find that reducing the cycling of the battery via introducing a penalty cost in the objective function of the energy arbitrage optimization model can improve the profitability over the life of the BESS.

1. Introduction

Battery energy storage systems (BESSs) are receiving more attention with increasing amounts of electricity produced by variable renewable energy sources like wind and solar, as BESS can address a range of challenges related to the uncertainty and variability in such resources ([1–3]). Therefore, it is important to analyze the profitability and potential for investment in BESSs. The idea behind energy arbitrage is to take advantage of daily energy price differences in order to buy cheap energy available during periods of low demand and store this energy in the battery. This low priced energy can then be sold at higher prices during peak load when prices are high (cf. [4]). Although there are many potential grid-level applications of BESS [5], energy arbitrage represents the largest profit opportunity for BESS in the electric power grid and is therefore an important application. BESS can also provide ancillary services, like spinning reserves and frequency regulation, but the markets for ancillary services are much smaller than the energy market. There are many recent studies on energy arbitrage modeling investigating the most profitable charging and discharging schedule for the storage device based on electricity market prices (e.g. [6–12]). Assumptions about battery lifetime and degradation are crucial to obtain realistic estimates of profitability. However, these issues are typically not addressed in detail in the energy arbitrage literature. One exception is the recent paper by Mohsenian-Rad [13], where a simple representation of lifetime effects on the optimal arbitrage schedule is proposed by introducing a constraint on the number of daily battery cycles. However, the impact on lifetime profitability is not considered. The analysis in Abdulla et al. [14] indicates that degradation has a substantial impact on battery lifetime and economic value for a residential BESS with solar PV under a fixed tariff scheme.

This paper expands on previous literature by proposing a new energy arbitrage model which explicitly represents battery degradation. This enables the investigation of different scenarios for battery degradation and their impact on achievable profit from energy arbitrage, as well as of how battery operation should be

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Nomenclature

Indices
t Time period (h)

Parameters
$P^{RT}(t)$ Real-time energy price in period t ($/MWh)
η_{to} Charging efficiency (including battery and system losses)
η_{from} Discharging efficiency (including battery and system losses)
η_{ch} Battery charging efficiency
η_{dis} Battery discharging efficiency
η_{sys} Efficiency of power converting system
U_{OCV} Open circuit voltage (V)
V_{ch} Charging voltage (V)
V_{dis} Discharging voltage (V)
I_{ch} Charging current density (A/cm^2)
I_{dis} Discharging current density (A/cm^2)
R Area specific resistance of the battery (Ωcm^2)
l Loading (Ah/cm^2)
eol End of life battery (fraction of initial battery capacity)
C^{ch} Max. rate of charge (1/h)
C^{dis} Max. rate of discharge (1/h)
SOC_{min} Min. state of charge
SOC_{max} Max. state of charge
SOC_0 Initial state of charge
f_B Battery fade constant (1/MWh)
c_B Battery penalty cost ($/MWh)
Q_B Initial battery capacity (MWh)
i Interest rate

Variables
$E^P(t)$ Energy purchased in period t (MWh)
$E^S(t)$ Energy sold in period t (MWh)
$E^{to}(t)$ Energy charged to battery in period t (MWh)
$E^{from}(t)$ Energy discharged from battery in period t (MWh)
$SOC(t)$ State of charge, end of period t (MWh)
$ID_{ch}(t)$ Binary battery charging indicator (0,1)
$ID_{dis}(t)$ Binary battery discharging indicator (0,1)
$TE(t)$ Total processed energy (from start to period t) (MWh)
$\Delta D(t)$ Degradation step in period t
$D(t)$ Summation of degradation steps
$DOD(t)$ $Q_{rem}(t)$
$Q_{rem}(t)$ Normalized remaining battery capacity in period t (fraction of Q_B)
$SOC_{max}(t)$ Max. state of charge in period t (MWh)
$\Delta c(t)$ Degradation penalty cost in time period t ($)
Π_y Annual net operating revenues in year y
NPV Net present value of revenue stream over useful lifetime of battery

adjusted to account for these effects. A better understanding of degradation on BESS lifetime and profitability is critical for investors in battery technologies and for improved evaluation of the potential future role for BESS in the electric power grid. Given that the focus of the paper is on battery degradation, we use standard and relatively simple assumptions for other aspects of the energy arbitrage problem, including perfect foresight about electricity market prices and constant battery efficiency. This provides us with a fast analytical tool for energy arbitrage analysis that enables us to analyze the importance of representing battery degradation and aging in such tools.

The rest of the paper has the following structure: Section 2 introduces relevant basic characteristics of Li-ion batteries. Section 3 describes the proposed energy arbitrage model, including two different representations of battery degradation. Section 4 presents a comprehensive case study of BESS profitability with different degradation models, using real-time electricity market prices from a selected location in the Midcontinent Independent System Operator (MISO) market. Conclusions and directions for future work are provided in Section 5.

2. Li-ion batteries: cost and degradation

Li-ion batteries are a relatively mature technology that is promising for grid storage applications due to high power and energy densities in combination with good cycle life and efficiency. However, high system capital costs as well as uncertainty about the lifetime remain important obstacles for a large-scale expansion of this technology in the grid. The capital cost of an energy storage system is composed of the battery cells, the balance of plant to maintain safe operation of the cells, the power conditioning system, and site installation. Operation and maintenance costs add an additional complication to the economics, which are ignored in this first order analysis. For Li-ion, the reported all-in capital costs have ranged from 500 to 1500 $/kWh ([3,1]). The large range in capital cost reflects the immature market, but also important differences in energy storage system design. Systems designed for longer storage durations (e.g. 5 h vs 1 h) will have a lower normalized capital cost as some components have a set power cost ($/kW), which appears less significant for longer durations. Longer time duration Li-ion batteries often are less expensive on a per energy basis than their shorter time duration (i.e. higher power density) alternatives. The least expensive Li-ion cells often are challenged from a cycle life perspective. In other words, an energy storage system that undergoes daily or even more frequent cycling will use a cell design and material choice that may have higher initial cost, but result in greater energy throughput over the life of the system. The capital cost of the energy storage systems appears to be on a downward trend owing both to decreasing Li-ion cell costs as well as classical experience curve effects [1] for building energy storage systems.

The lifetime of Li-ion batteries is limited due to unwanted side reactions which lead to a decrease of capacity and an increase in cell impedance [15]. The lifetime is strongly related to the battery chemistry and BESS operation. A major contribution to degradation for batteries with graphite anodes is the decomposition of the electrolyte and the irreversible consummation of lithium during cycling resulting in the growth of the solid-electrolyte interphase [1]. These processes depend on various factors like depth of discharge (DOD), state of charge (SOC), temperature (T), battery application, charging/discharging rate (C-rate), type of battery and manufacturer. It has also been observed that Li-ion battery degradation tends to accelerate at some point [16], and this has implications for its useful life. In this work, two different types of Li-ion batteries are investigated: the cathode of type 1 is $LiFePO_4$ (LFP), type 2 has a $LiNi_{1-x-y}Co_xAl_yO_2$ (NCA) cathode. In both cases, the cells have graphite anodes. The properties of the materials are different. LFP batteries show less dependency of aging on DOD and are considered to have greater abuse tolerance compared to those based on NCA. NCA batteries show a high energy density and better calendar lifetime especially at high temperatures.

As the interplay of the different degradation factors impedes a separation of the individual contributions, a common attempt of describing the degradation of the battery are simplified models counting the energy ([17,18]) or the charge throughput ([19,20]) of the battery. In these representations of degradation, the capacity of the battery decreases with increasing amount of processed energy (Wh) or charge (Ah) based on empirical results. Contributions to aging like an increase of the cell impedance (resistance) or calendar aging are not specifically taken into account. The models in [17,18,20] focus on an investigation of the battery degradation used in the electrical vehicle sector, whereas [19] performs a generalized cycle-life test. Apart from [17] with a vehicle to grid application, we are not aware of any applications of battery degradation specifically to energy arbitrage use.

This work focuses on estimating BESS arbitrage profitability considering several battery degradation models under different operational conditions. Under energy arbitrage, energy is purchased and sold in MWhs from the electricity market. Hence, we concentrate on energy throughput models to describe the battery degradation.

3. Energy arbitrage model with battery degradation

Finding the best operational strategy for energy arbitrage can be framed as an optimization problem. Since the focus of our study is on the impact of battery degradation, we use a simple energy arbitrage model. The basic assumptions for the model are that electricity prices are known in advance, i.e. the battery energy storage owner has perfect foresight and does not influence prices. Previous analyses of energy arbitrage profits from the PJM market [7,12] indicate that the perfect foresight assumption for prices overestimates the arbitrage revenue, but only with a modest amount (10–15%) compared to simple, but more realistic strategies where battery trading is based on backcasting of recent historical prices. The price-taker assumption is reasonable for small installations of BESS, as they are not likely to influence the electricity market. We also assume that the battery trades in the real-time electricity market, which typically has the highest volatility and therefore represent the best profit opportunity for energy arbitrage. The time resolution of the model is one hour, which corresponds to the time resolution of prices used for the financial settlement in the MISO electricity market in the United States. Finally, efficiencies and charging/discharging limits are all assumed to be constant. The model parameters and constraints of the optimization model are described below.

3.1. Objective function

The objective is to achieve maximal BESS profit from energy arbitrage over a given time period, T:

$$max\sum_{t=1}^{T}P^{RT}(t)\left(E^{S}(t)-E^{P}(t)\right)-\Delta c(t) \tag{1}$$

where $E^S(t)$ and $E^P(t)$ are sold and purchased energy, respectively, and $P^{RT}(t)$ is the hourly real time price of electricity. $\Delta c(t)$ represents the degradation penalty cost of the battery, which will be explained in Section 3.5.

3.2. Model constraints

To describe a battery different parameters like capacity, state of charge, maximum charging and discharging rate and charging and discharging efficiency are used, see e.g. [6,12]. Our implementation of the energy arbitrage model constraints are explained below. The state of charge of the battery at a specific time depends on the previous state of charge of the battery and the amount of energy moved from or to the battery:

$$SOC(t)=SOC_0-E^{from}(t)+E^{to}(t)\quad t=1 \tag{2}$$

$$SOC(t)=SOC(t-1)-E^{from}(t)+E^{to}(t)\quad t>1 \tag{3}$$

where $SOC(t)$ is the state of charge after period t, SOC_0 is the initial state of charge, $E^{from}(t)$ and $E^{to}(t)$ are the amounts of energy discharged from or charged to the battery, respectively.

The energy that can be charged to the battery or discharged from it is limited by the maximal charging and discharging rates (C^{ch} and C^{dis}) and the battery capacity Q_B:

$$E^{to}(t)\le Q_B\cdot 1h\cdot C^{ch}\cdot ID_{ch}(t)\quad\forall t \tag{4}$$

$$E^{from}(t)\le Q_B\cdot 1h\cdot C^{dis}\cdot ID_{dis}(t)\quad\forall t \tag{5}$$

where $ID_{ch}(t)$ and $ID_{dis}(t)$ are binary variables. Note that these binary variables were introduced to prevent charging and discharging of the battery to take place at the same time, which could otherwise occur during negative prices. Only one of the binary variables can have the value 1 at any given point in time:

$$ID_{ch}(t)+ID_{dis}(t)\le 1\quad\forall t \tag{6}$$

The losses of energy conversion during charging and discharging of the battery are taken into account introducing the efficiencies for charging and discharging energy (η_{to} and η_{from}) which will be described in Section 3.3 :

$$E^{P}(t)=E^{to}(t)/\eta_{to}\quad\forall t \tag{7}$$

$$E^{S}(t)=E^{from}(t)\cdot\eta_{from}\quad\forall t \tag{8}$$

where $E^P(t)$ and $E^S(t)$ are the amount of energy purchased and sold from/to the electricity market at a specific time t.

The current state of charge must be within a defined window, higher or equal to the minimal state of charge SOC_{min} and lower or equal to the maximal state of charge SOC_{max}:

$$SOC_{min}\le SOC(t)\le SOC_{max}(t)\quad\forall t \tag{9}$$

To keep track of the amount of total energy processed by the battery, the amount of energy discharged from the storage is accumulated:

$$TE(t)=E^{from}(t)\quad t=1 \tag{10}$$

$$TE(t)=TE(t-1)+E^{from}(t)\quad t>1 \tag{11}$$

The optimization model described by the objective function in (1) subject to the constraints in (2)–(11) amount to a mixed integer linear programming (MILP) problem that can be solved with standard mathematical programming solvers.

3.3. Battery efficiency calculations

The overall efficiencies of charging and discharging energy are dependent on battery charging/discharging efficiencies (η_{ch}/η_{dis}) and the efficiency of the power converting and heating/cooling system, η_{sys}(assumed to be 0.94):

$$\eta_{to}=\eta_{sys}/\eta_{ch} \tag{12}$$

$$\eta_{from} = \eta_{sys} \cdot \eta_{dis} \tag{13}$$

The charging and discharging efficiencies of the battery depend on the average open circuit voltage[1] U_{OCV} and the average charging and discharging voltages (V_{ch} and V_{dis}):

$$\eta_{ch} = V_{ch}/U_{OCV} \tag{14}$$

$$\eta_{dis} = V_{dis}/U_{OCV} \tag{15}$$

The charging and discharging voltages can be expressed as:

$$V_{ch} = U_{OCV} + I_{ch} \cdot R \tag{16}$$

$$V_{dis} = U_{OCV} - I_{dis} \cdot R \tag{17}$$

where $R = 60\,\Omega\text{cm}^2$ is the area specific resistance of the battery for continuous operation longer than 3 min in duration and I_{ch} and I_{dis} are the charging and discharging current densities:

$$I_{ch} = C^{ch} \cdot l \tag{18}$$

$$I_{dis} = C^{dis} \cdot l \tag{19}$$

The loading l is a fixed model parameter assuming $l = 1mAh/cm^2$ for LFP batteries and $l = 2mAh/cm^2$ for NCA batteries, which are common values for high to moderate power designs for these chemistries [21].

Calculating the round trip efficiency for the energy conversion, assuming a C-rate of $C^{ch} = C^{dis} = 1/h$, leads to an AC/AC roundtrip efficiency of 85% for LFP and 83% for NCA battery systems. A less conservative choice for one-way system efficiency of 0.97 would increase roundtrip values by ~6%.

3.4. Simulation setup

We use the arbitrage model to simulate battery operations for energy arbitrage chronologically over a period of up to 10 years, which is assumed to be the maximum calendar lifetime of the battery. It is not computationally feasible to solve the MILP problem for a time horizon of 10 years. The model is therefore optimized for 48 h at a time (i.e. $T = 48$).[2] However, only the results of the scheduling period for the first 24 h are used. This is to account for battery operations beyond the scheduling period and the inter-temporal constraints in energy storage level that will affect operations in the next period. The values of processed energy, remaining capacity, and state of charge after 24 h are transferred to the next day of the simulation. Then, the next 48 h are optimized, the results for the first 24 h are stored, and the process continues until 10 years of optimization is performed. The simulation set-up follows the standard daily scheduling cycle used in electricity markets.

In the case study, we used real-time market prices (cf. Fig. 1) for a specific transmission node in the MISO market. This node has high price variability which makes it a suitable location for energy arbitrage. For simplicity, the simulation uses the same market prices, i.e. for the year 2013, for all 10 years of the simulation. For better illustration, Fig. 2 shows the real-time market prices for a specific week. As can be seen, high price differences occur almost every day in this week, and negative prices are also observed.

The discounted revenue over the lifetime of the battery was calculated using the following formula:

$$NPV = \sum_{y=1}^{10} \frac{\Pi_y}{(1+i)^y} \tag{20}$$

where $\Pi_y = \sum_{t=1}^{8760} P^{RT}(t)\left(E^{S,y}(t) - E^{P,y}(t)\right)$ is the annual operating revenues for the battery. Note that energy purchases and sales are set to zero once the battery reaches the end of its lifetime, as defined in the next Section.

The simulation and underlying optimization model was implemented in the optimization software LINGO [23].

3.5. Degradation models

3.5.1. Model 0

Model 0 considers the case of an optimal battery with no degradation. As a result, no change of usable capacity occurs during operation. This leads to $\Delta c(t) = 0$ in the objective function (cf. Eq. (1)).

3.5.2. Model A

Model A takes the work of Peterson et al. [17] as a basis to describe the degradation of the battery. There, a LFP battery from A123 systems (ANR26650M1) was investigated simulating typical driving cycles for plug-in hybrid electric vehicles in combination with vehicle to grid services. As the results showed a degradation independent of the DOD, the authors introduced a Wh-model for arbitrage use (vehicle to grid) to describe the battery degradation. An adaption to this work leads to a formula for remaining battery capacity:

$$Q_{rem}(t) = 1 - f_{B,A} \cdot TE(t)/Q_B \quad \forall t \tag{21}$$

where $f_{B,A}$ is the battery degradation fade factor for model A, estimated to be $2.71 \cdot 10^{-5}$ in [17], $TE(t)$ is the total amount of processed energy, and Q_B is the initial battery capacity. As the reference illustrated no dependency of the degradation on the DOD, Model A uses the maximal available capacity resulting in $SOC_{min} = 0$ and $SOC_{max}(t) = Q_B \cdot Q_{rem}(t)$. However, the amount of storable energy is decreasing with every cycle due to degradation of the battery. In the context of this paper, two different scenarios for model A were investigated as described in the following.

Model A1: Model A1 assumes that the degradation of the battery does not affect the way the storage is operated. Therefore, the degradation penalty cost of the battery is not implemented in the objective function for optimization resulting in $\Delta c = 0$in Eq. (1). This leads to more frequent cycles of the battery than model A2 because use of the battery for arbitrage is triggered at smaller energy price differences, as discussed in more detail later.

Model A2: In model A2 the degradation of the battery is part of the operational strategy so it is implemented in the objective function in Eq. (1). Knowing the capacity degradation criterion for end of life (eol), i.e. the fraction of the initial capacity, Q_B, where the battery is no longer deemed usable for energy arbitrage purposes, a penalty cost for degradation for every cycled Wh can be defined resulting in the following term for Eq. (1):

$$\Delta c(t) = f_{B,A} \cdot E^{from}(t) \cdot \frac{c_B}{1 - eol} \quad \forall t \tag{22}$$

where c_B is a battery penalty cost (\$/MWh). Note that there is no need to count the energy throughput twice ($E^{from}(t) + E^{to}(t)$), so we

[1] The average open circuit voltage was assumed to be 3.68 V for the NCA battery and 3.28 V for the LFP battery [21].

[2] We experimented with a longer optimization period (T = 72 h), but this did not give significant changes in the results. Hence, we used T = 48 in the case study.

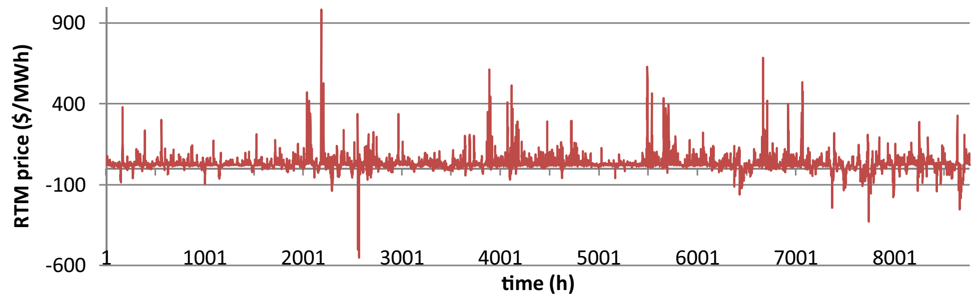

Fig. 1. Hourly real-time energy prices in 2013 for the node ALTW.FAIR.ST in the MISO electricity market.
Source: MISO [22].

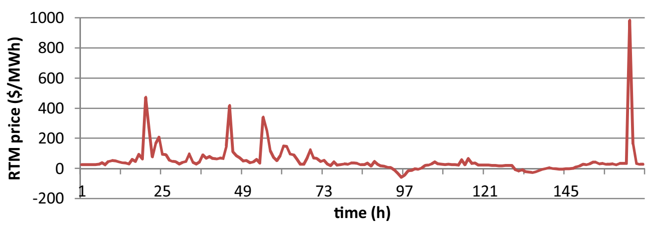

Fig. 2. Hourly real-time energy prices for the week 3/26/2013-4/1/2013 for the node ALTW.FAIR.ST in the MISO electricity market.
Source: MISO [22].

chose $E^{from}(t)$ to represent degradation. Eq. (22) will lead to less cycling of the battery because higher price differences between buying and selling will be needed to start operation. Ortega-Vazquez [23] proposes a similar degradation cost equation and sets c_B equal to the investment cost of the battery. However, since c_B influences the operational scheduling and the revenue stream as well as the resulting lifetime of the battery, several additional factors should be considered when setting the battery penalty cost. In the case study below, we conduct numerical simulations to identify the optimal battery penalty cost level for the specific assumptions used in this paper.

3.5.3. Model B

The basis for model B is the analysis of a NCA battery by Watanabe et al. [24]. There, the capacity fade was investigated at a temperature of 25 °C using a charging/discharging rate of 1C. A large impact on degradation of the used DOD-range was measured leading to a distinct higher cycle life when only using a range of 10–70% DOD. As the degradation showed a linear behavior within the 10–70% DOD range, for this work a linear fit of the data was performed to estimate the battery fade constant in model B, $f_{B,B}$, equal to $3.37 \cdot 10^{-5}$, resulting in the following degradation model:

$$Q_{rem}(t) = 1 - f_{B,B} \cdot TE(t)/Q_B \quad \forall t \tag{23}$$

As performed in [24], the usable SOC-range was adjusted to $SOC_{min} = 0.3$ and $SOC_{max}(t) = 0.9$ (constant for all t). Because of the limitation of the SOC-window the model does assume no fade in usable capacity during battery degradation. Hence, the initial usable capacity is only 60% compared to the other models but is not reduced during operation.

The same two different scenarios were investigated leading to $\Delta c(t) = 0$ for model B1 and

$$\Delta c(t) = f_{B,B} \cdot \frac{E^{from}(t)}{SOC_{max} - SOC_{min}} \cdot \frac{c_B}{1 - eol} \quad \forall t \tag{24}$$

for model B2.

The term $SOC_{max} - SOC_{min}$ is a result of the reduced SOC-window. As the degradation in [24] was defined by number of cycles, this dependency was transferred to the Wh- model: The number of cycles was multiplied by the processed Wh per cycle. Note that the battery penalty cost, c_B, has the same interpretation as in model A2 (Eq. (21)).

3.5.4. End of life criteria

The degradation models described above represent the capacity fade of the battery, and corresponding degradation cost, due to the use of the battery. The decay is assumed to be a linear function of energy throughput. However, real-world experience indicate that at some point decay tends to accelerate [16]. At this point, the battery degrades much faster, the linear assumption does no longer apply, and the remaining lifetime is very limited. We therefore define one EOL criterion to be when the remaining fraction of the battery capacity reaches a certain level, *eol*. In the case study, we analyze two different *eol* values, i.e. 80% of the initial capacity ([16,17,25,26]) or 65% [27] of initial capacity. The two values can be interpreted as a conservative and an optimistic assumption for when the onset of rapid degradation occurs.

Additional factors also influence battery degradation and lifetime. One important aspect is the calendar life of the battery. In the case study, we therefore impose an additional EOL criterion, i.e. the maximum calendar life of the battery. Large-scale applications of batteries in the power grid have a relatively short history with limited empirical data on battery lifetime. However, the use of batteries in electric and plug-in electric vehicles is more mature. The most common battery warranty length for vehicle applications is 8 years, although some manufacturers offer longer lifetime warranties.[3] We therefore assume that the maximum calendar life for the energy arbitrage application in the power grid is limited to 10 years. In the simulations, the end of the battery life therefore occurs, either when the remaining battery capacity reaches the defined *eol* value or when the maximum calendar life of 10 years is reached, whatever occurs first. Other degradation factors, such as temperature, are not represented in the analysis.

4. Results

Using the analytical framework described in Section 3, we analyze several cases related to degradation and EOL effects, using the ideal no degradation model as a benchmark. First, as explained in Section 3.5, we investigate two different operational strategies: i) the degradation penalty function is not implemented in the optimization function ($\Delta c(t) = 0$, model A1 and B1) and ii) the degradation penalty function is considered in the optimization

[3] For anover view of current warranty lengths for batteries in plug-in electric and electric vehicles we refer to http://energy.gov/eere/vehicles/fact-913-february-22-2016-most-common-warranty-plug-vehicle-batteries-8-years100000.

function (model A2 and B2). Moreover, we consider different EOL criteria, as discussed above. Finally, the C-rates of the battery in the different simulation scenarios were varied (1C, C/2, C/3 and C/4).

4.1. No degradation/model 0

This Section presents results from the energy arbitrage model under the ideal assumption of no battery degradation (cf. model 0, Section 3.5.1). As there is no degradation, the simulation ends at the EOL criterion of 10 years. Fig. 3 shows the processed energy at different C-rates of the battery. The processed energy decreases with increasing charging/discharging time of the battery (corresponding to lower C-rates), because at lower C-rates there is less opportunity to fully utilize the battery capacity under the most favorable price differentials. The impact on the net present value (NPV) of the revenue stream from energy arbitrage (i.e. not accounting for the investment cost) is also shown in Fig. 3. Irrespective of the chosen interest rate, the NPV decreases with longer charging/discharging time showing a correlation to the processed energy. Note that the NPV can be interpreted as the break-even investment cost where energy storage becomes profitable for the given historical energy prices.

The analysis shows that even when assuming no degradation of the battery the target break-even system cost at 1C is only 358 $/kWh (10% interest rate) and 409 $/kWh (7% interest rate). Comparing these NPVs to a battery cost of e.g. 500–1500 $/kWh as reported in [27] shows that investing in storage for arbitrage is not profitable at the moment for the assumptions used in this case study, even though we selected a location with high price variability. Still, alternative locations with higher and more variable electricity prices and the provision of several grid applications that generate multiple values streams present opportunities that may allow for market penetration of energy storage technologies already at today's costs [3]. In addition, prices for storage devices are forecasted to decrease over time. A recent U. S. Department of Energy report targets the total system capital cost for grid energy storage to less than 250 $/kWh with a long-term goal of 150 $/kWh [28]. At these target cost levels, energy storage would be profitable at the selected location at today's electricity market prices assuming no degradation. In the next Section, we investigate the impact of degradation on the battery's NPV of the revenue stream from energy arbitrage.

4.2. Degradation

4.2.1. Results for model A

First, the battery degradation model A1 is implemented as described in Section 3.5.2. Fig. 4 shows the processed energy at different C-rates. As a result of the capacity fade, less energy is processed compared to the no-degradation-case (cf. Fig. 3). With

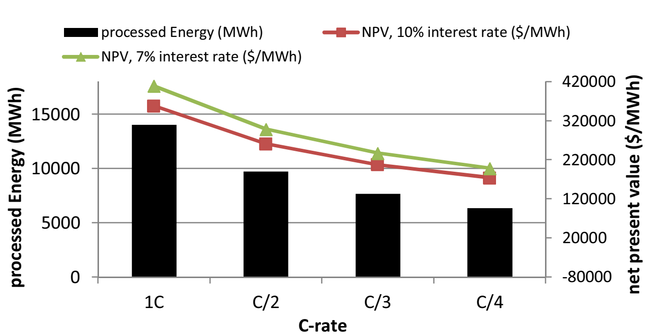

Fig. 3. Processed energy (TE) and net present value (NPV) per installed MWh at different C-rates during 10 years of operation assuming no degradation.

eol defined at 80%, this EOL criterion dominates for 1C and C/2 because in those cases 80% of the initial capacity is reached before the 10 year EOL criterion. Choosing 65% of initial capacity as the *eol* value allows operation of the battery over the full time period of 10 years. For C-rates of C/3 and C/4 the battery is operated for the full 10 years under both *eol* values, because the capacity EOL criterion is not reached.

Similar to the processed energy, the NPV of model A1 is less than in model 0 where no degradation is assumed (cf. Fig. 4). For example, at an interest rate of 10% for a 1C battery, the NPV is 225 $/kWh (80%/10years) or 306 $/kWh (65%/10 years) compared to 358 $/kWh in the no degradation case (cf. Fig. 3).

The results presented so far assume no degradation penalty cost in the objective function (model A1). An important question is whether such a penalty cost for battery degradation could lead to an increase in achievable profit over the lifetime of the battery. Therefore, different values for the battery penalty cost c_B (see Eq. (22) in Section 3.5.2) were used (i.e. 100,000 $/MWh–700,000 $/MWh) in model A2.[4] Fig. 5 shows that the processed energy is strongly dependent, not only on the chosen EOL criteria and C-rate, but also on the battery penalty cost. In general, adding a battery penalty cost leads to less cycling of the battery (less processed energy) because the penalty cost in the objective function (Eq. (1)) prevents cycling from occurring during small price differences. As a result, the battery could be operated during the full 10 years, independently of the *eol* value for all the penalty cost levels tested. Hence, because of a longer battery lifetime with the penalty costs, high price differences can be exploited at a time where in model A1 ($c_B = 0\$/\mathrm{MWh}$) EOL is already reached. This advantage of longer lifetime due to reduced battery use will have to be weighed against lower profits in the initial periods and the fact that in the NPV analysis profits in the early periods are more important due to the discounting of future cash flows.

Fig. 6 shows a comparison of the achieved NPV for the different scenarios of model A1 and A2. With the exception of C-rate C/2 at the 65%/10 years EOL criteria, the highest NPV value was always achieved with the penalty cost, c_B, of 100,000 $/MWh. The largest NPV overall is observed for a C-rate of 1C (65%/10 years EOL criteria) followed by 1C (80%/10 years EOL criteria), under a battery penalty cost of 100,000 $/MWh. A further comparison of the different NPVs across all different models is provided in Section 4.3. The hourly evolution of the capacity and processed energy during the 10 years of simulated battery operation is visualized in Fig. 7. A battery penalty cost of 100,000 $/MWh (model A2) is compared to the case assuming no penalty cost (model A1). The graph shows a stronger decrease of capacity over time in the case of model A1 because of the higher amount of processed energy. Comparing these results to the NPV provided in Fig. 6 reveals that even with less processed energy in model A2 the NPV is higher compared to A1 (for $c_B = 100,000\$/\mathrm{MWh}$) $/MWh in model A2. The reason is that available capacity is less in model A1 at later times due to the fact that this model arbitrages even when the hourly price differences are small in early years. This increases the battery degradation and reduces available capacity thereby reducing the opportunity to benefit from arbitrage at higher price differentials in later years. This is the case even with the 65% *eol* value, which is

[4] Note that in the results presented here we assume that c_B is a constant. In principle, this does not need to be the case. For instance, we ran some sensitivity cases where we used a dynamic c_B, which was adjusted to increase according to the discount rate, since revenues in the early years count more than in later years in the NPV calculation. However, this did not give significant changes in the total profit over the lifetime of the battery compared to the case with a fixed c_B. We therefore focus on the cases with fixed c_B.

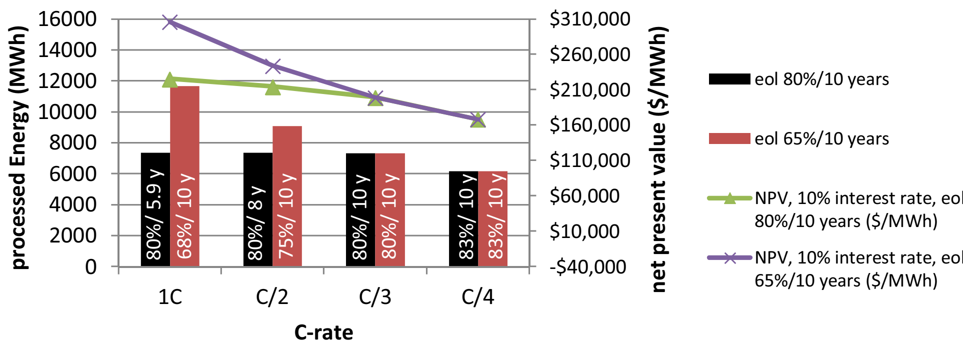

Fig. 4. Model A1: processed energy (TE) and NPV per installed MWh at different C-rates and EOL criteria. The text in white shows the remaining capacity at EOL and when the binding EOL criterion is reached.

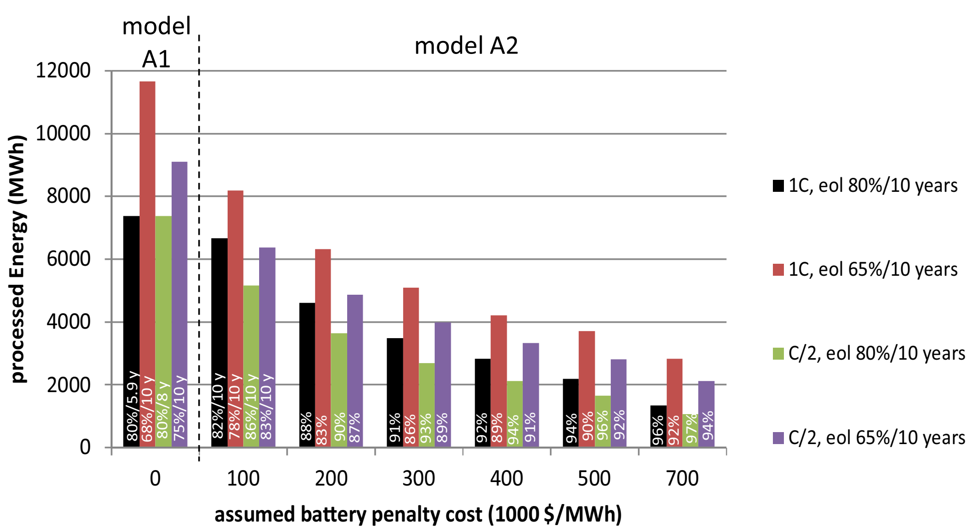

Fig. 5. Comparison of model A1 (i.e. $c_B = 0$ $/MWh) with model A2 (i.e. $c_B > 0$ $/MWh) for C-rates 1C and C/2: processed energy (TE) per installed MWh at different assumed battery penalty cost, c_B, and EOL criteria. The text in white shows the remaining capacity when the binding EOL criterion is reached.

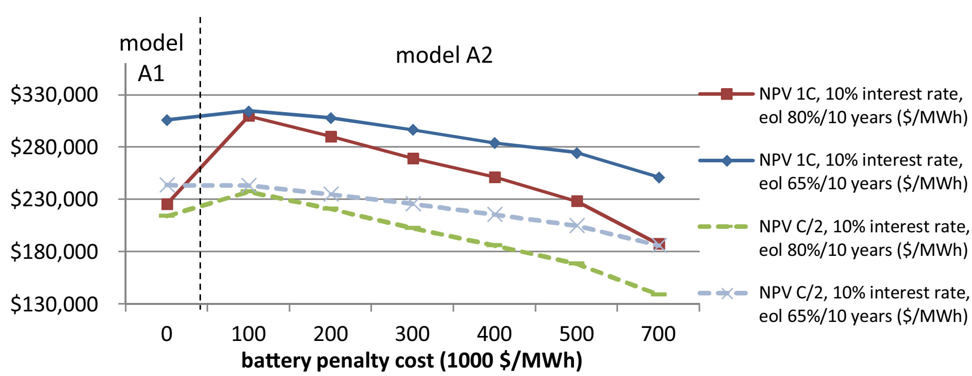

Fig. 6. Comparison of model A1 (i.e. $c_B = 0$ $/MWh) with model A2 (i.e. $c_B > 0$ $/MWh) for C-rates 1C and C/2: NPV per installed MWh for different battery penalty cost, c_B, and EOL criteria.

not reached during the 10 years simulation for any model, as shown in Fig. 7.

The development of profit over time is illustrated in Fig. 8. The figure shows that for the *eol* value of 0.8, the cumulative profit for model A1 (without penalty) is growing faster in the beginning of the 10 years period. However, in this case the cumulative profit levels out after only 6 years, since the *eol* value is reached. In contrast, with the $100 penalty the battery is able to operate throughout the 10 year period, and ends up with a substantially higher cumulative profit in the end. In the case of an *eol* value of 0.65, the profits in the models with and without penalty grow at similar pace in the first part of the period, but the profit for model

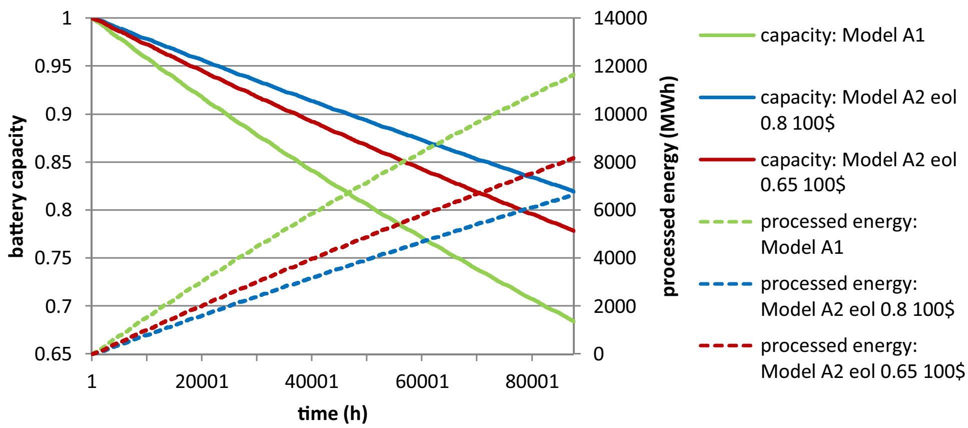

Fig. 7. Model A: Simulated evolution of remaining battery capacity and processed energy (TE) per installed MWh over 10 years for a C-rate of 1C.

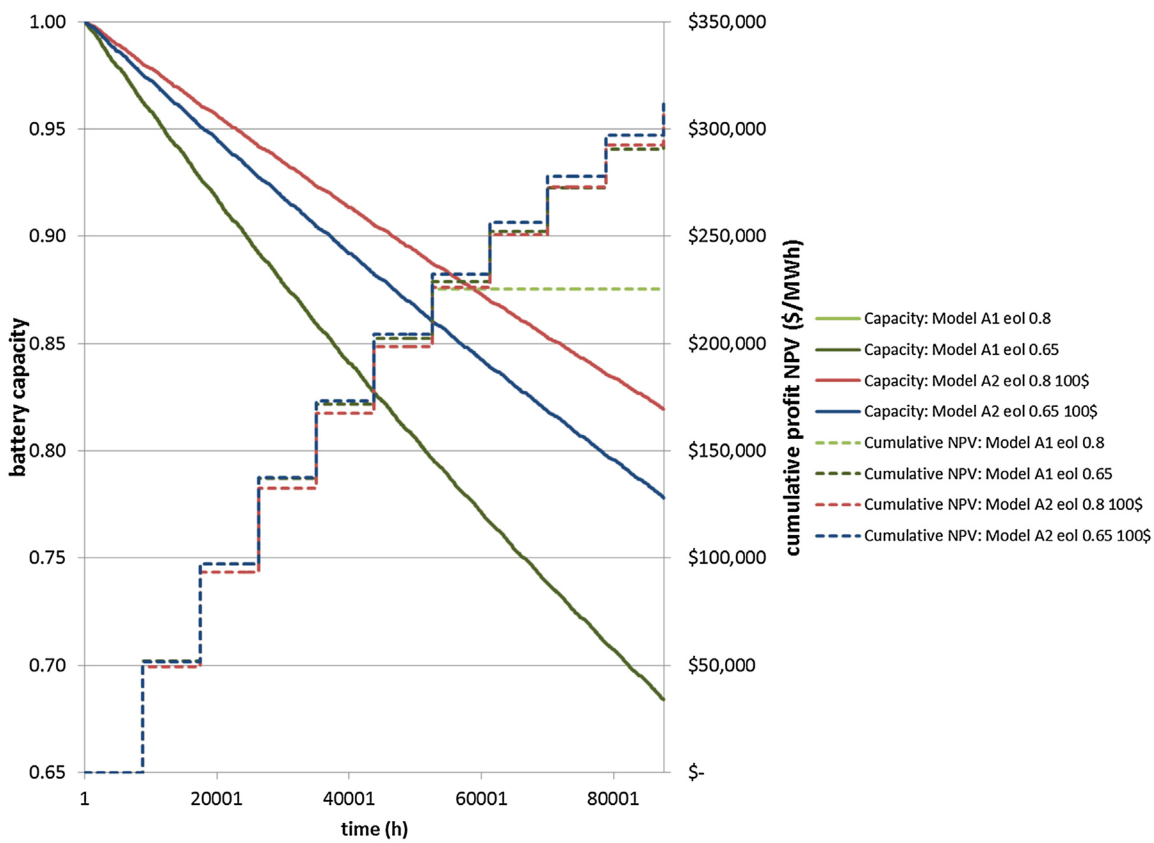

Fig. 8. Model A: Simulated evolution of remaining battery capacity and cumulative profit per installed MWh over 10 years for a C-rate of 1C.

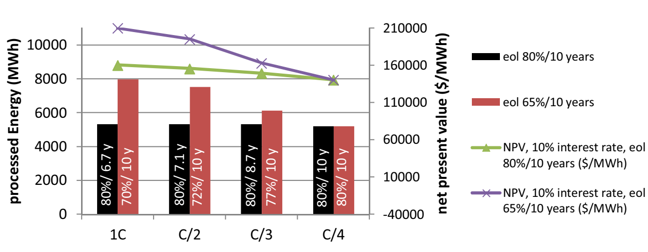

Fig. 9. Model B1: processed energy (TE) and NPV per installed MWh at different C-rates and EOL criteria. The text in white shows the remaining capacity at EOL and when the binding EOL criterion is reached.

A2 (with $100 penalty) grows faster towards the end since more capacity remains. Hence, Fig. 8 illustrates why a penalty in the objective function is optimal for both EOL criteria.

4.2.2. Results for model B

As described in Section 3.5.3, model B1, which applies to the NCA battery, uses only 60% of the battery capacity to increase battery lifetime. This constraint on available capacity results in a lower amount of processed energy (cf. Fig. 9) compared to model A1 (cf. Fig. 4). The amount of processed energy considering an EOL criteria of 80%/10 years is the same for C-rates of 1C, C/2 and C/3 because the capacity limit is reached as the EOL criterion and not the 10 year time limit. Choosing 65%/10 years as EOL criteria allows a battery operation over the full 10 years resulting in a higher

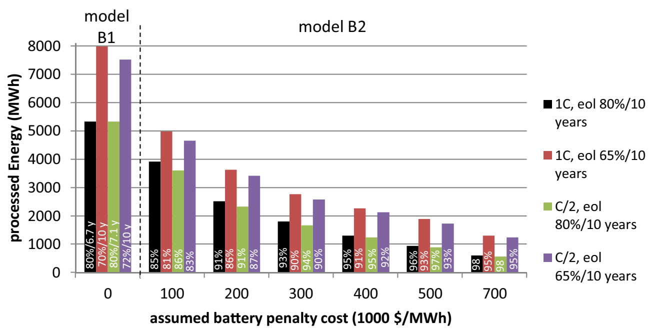

Fig. 10. Comparison of model B1 (i.e. $c_B = 0$ $/MWh) with model B2 (i.e. $c_B > 0$ $/MWh) for C-rates 1C and C/2: processed energy (TE) per installed MWh at different assumed battery penalty cost, c_B, and EOL criteria. The text in white shows the remaining capacity when the binding EOL criterion is reached.

amount of processed energy, especially for high C-rates. Fig. 9 also shows the NPV at different C-rates and interest rates. The characteristics exhibit a similar behavior compared to model A1 revealing the highest NPV at a C-rate of 1C. The NPV for model B1 in general is lower than for model A1 showing no case where NPV is higher or equal than 250 $/kWh (DOE's near-term system cost target [28]). The lower NPV is a result of the limited battery capacity used in model B. Assuming battery systems corresponding to model A and B have as similar installed capital cost per total system energy, then the difference in NPV would lead to selecting a system with the characteristics of A over B. In practice, installed capital costs will be different and a more complex valuation will be required.

The effect of introducing a penalty function into the objective function (cf. model B2 in Section 3.5.3) is also investigated for degradation model B. The amount of processed energy decreases with increasing battery penalty cost, as shown in Fig. 10. The NPV of the revenue stream (cf. Fig. 11) shows again the highest value for the battery penalty cost of 100,000 $/MWh at the 80%/10 years EOL criteria. For EOL criteria of 65%/10 years, the highest NPV is achieved without a penalty cost. The next Section provides a comparison of the results across all the different degradation models.

4.3. Comparison of degradation models

There is a high degree of uncertainty in the absolute numbers for battery profitability presented above, given the simplifying assumptions used in the energy arbitrage model as well as the fact that future energy prices are likely to deviate substantially from the past. Hence, in this Section we compare the simulated energy arbitrage revenues of the battery with the different degradation models and assumptions in relative terms (Table 1), using the revenue from the case with no degradation (model 0) as a benchmark. The results show that for an EOL criteria of 80%/10 years a modest degradation penalty of $100,000/MWh in the objective function always increases the NPV, i.e. the case for both degradation models and for both C-rates. The main reason is that the 80% capacity criteria is reached before 10 years in the case where no penalty function is applied due to a high amount of cycling even at lower price differentials. In contrast, the battery cycling occurs only at higher price differentials when a penalty cost is introduced. Therefore, with less cycling higher price differences can be exploited throughout the 10 years of potential battery lifetime and this increases the NPV. Table 1 also shows that the reduction in revenue due to degradation compared to the idealistic model 0 is 13.4% and 9.0% for model A at C-rates 1C and C/2, respectively, at the optimal battery penalty cost level of $100,000/MWh. For model B the corresponding revenue reductions due to degradation are as high as 45.7% and 31.0% at C-rates 1C and C/2, respectively.

The results with the EOL criteria of 65%/10 years show a different behavior. In this case, apart from model A at 1C, it is more profitable not to use a battery penalty cost in the objective function. The reason for this result is more complex. On the one hand, the battery lifetime is 10 years in all these cases because the *eol* value of 65% is not reached. Therefore, profit can be achieved during the full 10 year timeframe. On the other hand, more cycling leads to a stronger capacity fade. In the case of model A, there is less capacity available to achieve profit during times of large price differences in the latter parts of the 10 years period if the battery was cycled heavily in the first part of the period. In contrast, model B has no decrease of usable capacity since only a fraction of the full capacity is used. In sum, there is the relation between available capacity, cycling history, and price differences over time that contributes to the amount of achievable revenues and the corresponding lifetime NPV. For model A at 1C and 65%/10 years EOL criteria, without a penalty the amount of processed energy and corresponding capacity fade is too high and it reduces the amount of profit at a later time of operation too much. In contrast, the other cases investigated at the 65%/10 years EOL criteria achieve the highest profit without a degradation penalty. These results illustrate that no single rule applies for the optimal value of the battery degradation penalty as it depends on multiple factors, including battery (e.g. C-rate, EOL criteria), operational (e.g. whether the full or partial SOC range is used), and market (e.g. price variability) specific factors. Hence, the degradation penalty should be determined in every individual battery configuration and market scenario to maximize the NPV of revenue streams from energy arbitrage. Finally, Table 1 also shows that the reduction in

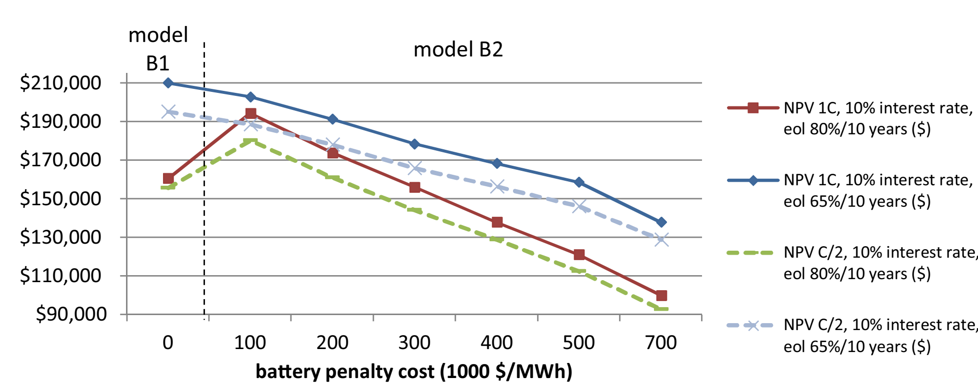

Fig. 11. Comparison of model B1 (i.e. $c_B = 0$ $/MWh) with model B2 (i.e. $c_B > 0$ $/MWh) for C-rates 1C and C/2: NPV per installed MWh for different battery penalty cost, c_B, and EOL criteria.

Table 1
Relative comparison of NPV at different EOL criteria and C-rates with different degradation models, using the NPV with no degradation (Model 0) as a benchmark. The penalty level achieving the highest NPV is highlighted in bold for each case.

battery penalty cost ($/MWh)	EOL criteria	% of maximum NPV			
		1C		C/2	
		Model A	Model B	Model A	Model B
0	80%/10 years	63.0	44.8	82.0	59.6
100,000		**86.6**	**54.3**	**91.0**	**69.0**
200,000		81.1	48.6	84.6	61.6
300,000		75.3	43.6	77.5	55.2
400,000		70.3	38.5	71.2	49.3
500,000		63.8	33.8	64.5	43.0
700,000		52.4	27.9	53.1	35.5
0	65%/10 years	85.6	**58.7**	**93.4**	**74.7**
100,000		**87.9**	56.7	93.2	72.1
200,000		86.1	53.4	90.1	68.2
300,000		82.9	49.9	86.5	63.5
400,000		79.5	47.0	82.7	59.9
500,000		76.8	44.3	78.5	56.0
700,000		70.3	38.5	71.2	49.3

revenue due to degradation is slightly lower with the 65% compared to the 80% *eol* value.

5. Conclusions and future work

In this study we investigated the impact of battery degradation on the potential revenue from energy arbitrage. The case study based on historical real-time price data from a location with high price variability in the MISO electricity market in the United States illustrated that battery degradation has a large impact on the achievable NPV of revenues from arbitrage operation. Using different degradation models based on two different battery chemistries, we found NPVs in the ranges of 194–310 $/kWh (EOL criteria 80%/10 years) or 209–314 $/kWh (EOL criteria 65%/10 years) for a battery with C-rate of 1C, assuming an interest rate of 10%. This compares to a NPV of 358 $/kWh in the idealistic case where no battery degradation is considered. Hence, we conclude in this analysis that the reduction in revenue due to degradation is in the 12–46% range depending on the degradation model and EOL criteria for a C-rate of 1C. The estimated NPVs are strongly dependent on the chosen degradation parameters as well as the EOL criteria. The analysis revealed that using a battery with characteristics of degradation model A (i.e. for a LFP battery) results in a higher revenue stream compared to a battery with characteristics of degradation model B (i.e. for a NCA battery) for an installation of equivalent total system energy. Our analysis also showed that adding a degradation penalty to the objective function of the arbitrage model to prevent cycling during small arbitrage opportunities can lead to a higher NPV. However, the level of degradation penalty that should be used depends on a number of factors and cannot be generalized.

The absolute numbers for energy arbitrage profitability are of course uncertain estimators for future profitability, given all the data and model assumptions that go into the analysis. However, the results clearly do illustrate the importance of integrating battery degradation into the analysis of battery profitability in order to better assess the cost-effectiveness of energy storage investments. The inclusion of degradation models into the energy arbitrage analysis also enables the assessment of the future cost levels that must be achieved for battery energy storage to become a viable economic investment. For instance, our results indicate that DOE's intermediate system cost target of 250 $/kWh [28] would be sufficient for energy arbitrage to become a profitable application of battery energy storage at favorable locations in the MISO electricity market based on historical prices.

In future work, we plan to further investigate the optimal value for the degradation penalty cost as a function of time and battery condition, and explore to what extent a simplified penalty cost function can capture the complex relationships between battery degradation and arbitrage profitability. Moreover, we plan to develop additional degradation models for a wider set of battery technologies. This includes models that explicitly consider degradation dependent on DOD of the battery to analyze in more detail whether shallow cycling of the storage system may result in a higher NPV. We will also consider an explicit representation of calendar aging. Finally, we plan to introduce the proposed set of degradation models into a wider set of power grid optimization models, including system-wide planning, scheduling, and dispatch.

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