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Energy Arbitrage Through Smart Scheduling of Battery Energy Storage Considering Battery Degradation and Electricity Price Forecasts

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***Abstract*—As a result of growing markets for electric vehicles and residential batteries for buffering energy from photovoltaics, the number of grid-integrated lithium-ion batteries has been continuously increasing in the past years. Apart from their primary purpose, these batteries may also be employed to provide services to the power grid in terms of peak shaving or frequency regulation. The profitability of such services for the battery owner, however, remains a controversial issue. Particularly battery degradation resulting from increased energy throughput is discussed as a major impediment for profitable operation. This paper presents a scheduling approach which considers the non-linear dependencies of battery aging from various operation parameters along with real-time prices and price forecasts for computing optimal charging/dispatching schedules. The methodology is applied to price-data obtained from four different electricity markets. The investigation partly confirms existing profitability concerns but further shows that explicit consideration of battery degradation can yield profitable outcomes. Various scenarios using aggregated and locational marginal prices as well as different forecasting horizons and time resolutions are explored to identify favorable operating conditions.**

***Index Terms*—batteries, battery degradation, electric vehicle, grid-integration, scheduling**

I. Introduction

Over the next decade, decreasing prices of lithium-ion batteries can be expected to foster the sales of both *plug-in electric vehicles* (PEV) and small-scale home batteries to private households [1]. While the primary purpose of these batteries is to serve mobility needs or to buffer excess energy generated from residential photovoltaics, grid integrated batteries may also be employed to provide services to the power grid. Through controlled charging or energy back-feeding, distributed energy storage could serve for shaving load peaks, filling load valleys, and balancing frequency fluctuations, thus facilitating the integration of renewable energies and mitigating possible grid congestion caused by uncontrolled PEV charging [2].

While the technical viability of this concept has been demonstrated in a great variety of studies particularly in the context of *vehicle-to-grid* (V2G) [3]–[6], notable doubts regarding its economic profitability remain [2], [7]–[14]. The main concern in this context is the degradation of batteries which may overcompensate revenues attainable in the electricity markets. A recent study in [15] concludes that peak shaving through V2G may result in a reduction of battery lifetime by approximately 3 years. Even more pessimistic are the conclusions drawn in [16] and [17] where it is argued that multiple battery replacements would be necessary during a vehicle's lifetime. A similar statement is made for the case of stationary batteries in [18] and [19] where the findings indicate that degradation costs considerably outweigh arbitrage revenues. Appropriately accounting for battery degradation is therefore crucial for profitable participation in the electricity market.

There are various charging techniques in related contexts accounting for battery degradation by limiting the *state of charge* (SOC) range [20]–[22] or restricting the *charge rate* (C-rate) [23]–[25]. Other recent approaches consider degradation as a function of the *SOC swing* ΔSOC (alternatively denoted *depth of discharge*) [26]–[30].

However, the static limitation of a battery's operation range without an underlying model makes the restriction somewhat arbitrary and therefore does not lead to an optimal outcome. The one-dimensional dependency on the SOC swing better accounts for degradation while keeping the optimization problem simple. It nevertheless neglects the fact that degradation does not only depend on how deep a cycle is but also in what voltage range (i.e., around what SOC) it occurs. This non-linear, two-dimensional dependency of degradation from SOC swing and voltage is explicitly considered by the proposed model employed as part of the presented scheduling approach. This allows taking into account the trade-off between marginal degradation costs and revenues at each point in time. The scheduling further relies on real-time electricity prices as well as price forecasts which allows trading off current costs with future revenues.

Based on this scheduling approach which is described in Section II, the paper presents a study employing battery storage for energy arbitrage in four different real-time markets. The

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objective of this study presented in Section III is to provide an insight into conditions under which energy arbitrage using small-scale batteries can be profitable. These findings shall add another perspective to the rather critical discussion of economic profitability established in the above cited work. Conclusions on the general conditions on profitability of batteries for energy arbitrage and the influence of different aspects such as battery investment costs, price forecast horizons, as well as temporal and spatial resolution of price data in the various markets are finally drawn in Section IV.

II. Scheduling Approach

The scheduling algorithm determines the behavior of a price-taking battery agent which attempts to maximize its profit Π by buying and selling energy in a real-time market. For this purpose, real-time electricity prices as well as price forecasts are exploited. As electricity prices are typically periodically updated, the problem can be discretized into distinct periods of duration Δt. The decision variable is the power P_i which can be set independently for any time period i. The outcome of the optimization is an optimal charging/dispatching schedule $\widetilde{P} = (P_1, P_2, ..., P_N)$ and a maximum possible profit $\tilde{\Pi}$.

A. Basic Problem Formulation

Considering battery capacity and C-rate constraints, maximum profits can be achieved by solving the following optimization problem:

$$\begin{aligned} \text{maximize} \quad & \Pi = \sum_{i \in \mathcal{H}} (r_i - c_i) && (1) \\ \text{subject to} \quad & P_{\text{min}} \leq P_i \leq P_{\text{max}} \quad \forall i && (2) \\ \text{and} \quad & 0 \leq SOC_i \leq 1. \quad \forall i && (3) \end{aligned}$$

Both revenues r_i and costs c_i are functions of the charging/discharging power P_i. Unlike in bang-bang control approaches, the power P_i can assume any value in an interval ranging from P_{min} to P_{max}. The possible range of power values is determined by the specification of the power connection and by the maximum charge/discharge rates of the battery. $P > 0$ describes the case where energy is transferred from the grid to the battery (G2B) and $P < 0$ the opposite case of feeding energy from the battery back to the grid (B2G). The power is measured from the perspective of the power grid so that the power P fed into the grid and the power drawn from the battery P_{Batt} are related through $P = P_{\text{Batt}} \cdot \eta_{\text{B2G}}^{-1}$. In this context, η_{B2G} describes the discharging efficiency which may generally be different from the charging efficiency η_{G2B}. Constraint (3) ensures that the battery's SOC remains between 0 and 1 avoiding deep discharges or overcharging. $\mathcal{H}$ denotes the time horizon which is subject to optimization. In reality, price data will, however, only be available for a subset $h \subset \mathcal{H}$ with h typically covering a time frame of several minutes to multiple hours. The problem is therefore treated as a *rolling horizon* problem in which a re-optimization is conducted once new information becomes available.

The revenue in a given time period i is determined by the electricity price p_i and the amount of energy being sold which is given by $P_i \cdot \Delta t$. The revenue in period i is therefore simply determined according to $r_i = p_i \cdot P_i \cdot \Delta t$.

The costs occurring in a period i consist of various factors including the price p_i for purchasing energy, energy dissipation costs due to efficiency losses, and, most importantly, battery degradation costs c_{D}. For transferring energy from the grid to the battery, the costs are given by

$$c_{\text{G2B},i} = (p_i + c_{\text{D}} \cdot \eta_{\text{G2B}}) \cdot |P_i| \cdot \Delta t. \tag{4}$$

Transferring energy from the battery to the grid does not include any purchase of electricity so that the costs are given by

$$c_{\text{B2G},i} = \left(\frac{c_{\text{D}}}{\eta_{\text{B2G}}} \right) \cdot |P_i| \cdot \Delta t. \tag{5}$$

As the power P is measured from the grid side, charging (discharging) energy losses according to $\eta_{\text{G2B/B2G}}$ cause the power flow through the battery to be smaller (greater) than P during charging (discharging). Therefore $\eta_{\text{G2B/B2G}}$ appears in the numerator in (4) and in the denominator in (5).

Assuming constant power during a period i, the SOC of a battery pack with capacity CAP_{BP} at the beginning of period $i+1$ is computed according to

$$SOC_{i+1} = SOC_i + \Delta SOC_{\text{G2B/B2G},i} \tag{6}$$

with

$$\begin{aligned} \Delta SOC_{\text{G2B},i} &= \frac{P_i \cdot \Delta t}{CAP_{\text{BP}}} \cdot \eta_{\text{G2B}} && (7) \\ \Delta SOC_{\text{B2G},i} &= \frac{P_i \cdot \Delta t}{CAP_{\text{BP}}} \cdot \frac{1}{\eta_{\text{B2G}}}. && (8) \end{aligned}$$

B. Battery Degradation Model

Battery degradation involves a decrease of capacity and a power fade, both of which result from calendar aging and cycling of energy. The related aging processes depend on various parameters including C-rate, SOC, ΔSOC, temperature, and humidity. In the context of the investigated application, capacity fade due to cycle aging can be considered the predominant process. Furthermore, only small C-rates mostly far below 1 C can be expected so that the most influential operation parameters are SOC and ΔSOC. The presented degradation model therefore focuses on these aspects. The model is abstracted from an empirical aging study presented in [31] and [32] which investigates the degradation of a $Li(NiMnCo)O_2$ based 18650 lithium-ion battery. It describes the decrease of the normalized capacity $cap \in [0, 1]$ as a function of the accumulated charge throughput Q as

$$cap(Q) = 1 - \beta \cdot \sqrt{Q} \tag{9}$$

with the parameter

$$\begin{aligned} \beta = \; & 7.348 \cdot 10^{-3} \cdot (\overline{U} - 3.667)^2 + 7.6 \cdot 10^{-4} + \\ & +4.081 \cdot 10^{-3} \cdot \Delta SOC. \end{aligned}$$

As an approximation, the average voltage $\overline{U}$ during a half-cycle from SOC_{start} to SOC_{end} can be retrieved from the battery's *open circuit voltage* (OCV) curve by taking the voltage at the beginning and the end of the half-cycle.

The total charge $Q_{\text{EOL,Cell}}$ which can be cycled through the cell with capacity CAP_{Cell} under a particular cycling regime until the battery reaches its *end of life* (EOL) can be computed by solving (9) for $cap(Q_{\text{EOL,Cell}}) = cap_{\text{EOL}}$. cap_{EOL} can be set according to the particular use case, e.g., to 0.8 for automotive use or to even lower values for stationary or second-life applications. The total cyclable energy is then given by $E_{\text{EOL,Cell}} = \overline{U} \cdot Q_{\text{EOL,Cell}}$. Scaling this amount from one cell to the entire battery pack with capacity CAP_{BP} yields $E_{\text{EOL,BP}} = E_{\text{EOL,Cell}}(CAP_{\text{BP}} \cdot CAP_{\text{Cell}}^{-1})$. This leads to the cost per cycled unit of energy

$$c_{\text{D}} = \frac{C_{\text{BP}}}{E_{\text{EOL,BP}}} = C_{\text{BP}} \cdot \frac{\beta^2}{(1 - cap_{\text{EOL}})^2 \cdot \overline{U}} \tag{10}$$

with C_{BP} denoting the cost of the battery pack. Through β and $\overline{U}$, this accounts for the dependency of cycle costs on SOC and ΔSOC. As in a real application every charge/discharge process occurs at different SOC and ΔSOC, each cycle is related to a different β so that $c_{\text{D,Cell}}$ is re-calculated whenever the cycling regime is changed.

C. Dynamic Programming Formulation and Solution Algorithm

Due to the non-linear dependency of battery costs from the operation parameters, the problem itself is also non-linear. To avoid a formulation as a mixed-integer non-linear program, it is solved using a *dynamic programming* algorithm [33]. This formulation leverages on the fact that the optimization over a series of time steps can be decomposed into smaller sub-problems which can be solved sequentially. The problem can be defined as a discrete-time dependent system where the discretization is given by the intervals in which prices are kept constant. The system is then described by the temporal development of its state

$$SOC_{i+1} = f_i(SOC_i, P_i), \qquad i = 0, 1, ..., N-1 \tag{11}$$

where f_i follows directly from (6), (7) and (8). The state SOC_i is an element of the state space S_i which, in accordance with restriction (3), is given by

$$S_i = \{SOC_i \in \mathbb{R} \,|\, 0 \leq SOC_i \leq 1\}. \tag{12}$$

The control variable P_i belongs to the control space

$$X_i = \{P_i \in \mathbb{R} \,|\, P_{\text{min}} \leq P_i \leq P_{\text{max}}\} \tag{13}$$

which is in accordance with restriction (2).

The possible values for P_i are further constrained to a subset $U(SOC_i) \subset X_i$ which depends upon the current state of the system SOC_i so that $P_i \in U_i(SOC_i)$ for all i and $SOC_i \in S_i$. As a result of the SOC constraint (12), this subset can be written as $U_i(SOC_i) = U_i^+(SOC_i) \cup U_i^-(SOC_i)$ with

$$U_i^+(SOC_i) = \{P_i \in \mathbb{R}_{\geq 0} \,|\, SOC_i + P_i \cdot \Delta t \cdot \eta_{\text{G2B}} \cdot CAP_{\text{BP}}^{-1} \leq 1\}$$

and

$$U_i^-(SOC_i) = \{P_i \in \mathbb{R}_{<0} \,|\, 0 \leq SOC_i + P_i \cdot \Delta t \cdot \eta_{\text{B2G}}^{-1} \cdot CAP_{\text{BP}}^{-1}\}.$$

The class of control policies can be expressed in the form $\gamma = \{\mu_0, ..., \mu_{N-1}\}$. In this expression, μ_i maps the states SOC_i into controls $P_i = \mu_i(SOC_i)$ in a way that $\mu_i(SOC_i) \in U_i(SOC_i)$ for all $SOC_i \in S_i$.

For given cost functions g_i, $i = 0, 1, ..., N$, the total cost J of a control strategy γ which starts at a state SOC_0 is

$$J_\gamma(SOC_0) = g_N(SOC_N) + \sum_{i=0}^{N-1} g_i(SOC_i, \mu_i(SOC_i)).$$

The cost function g_i in this case is simply defined by $-\pi = c_i - r_i$ as introduced in Section II. An optimal control strategy $\gamma*$ minimizes this cost so that

$$J_{\gamma*}(SOC_0) = \min_{\gamma \in \Gamma} J_\gamma(SOC_0) \tag{14}$$

with Γ representing the set of all admissible policies.

To solve this problem, the SOC is discretized into M steps so that the state can be written as SOC_i^k with $k = 0, 1, ..., M-1$. The computational requirements are proportional to the number of possible values of the state variable, therefore a reasonable trade-off between accuracy and computational efforts needs to be found in practice. The solution algorithm starts from the last state of the problem of which the costs are set to $J_N^k(SOC_N^k) = g_N^k(SOC_N^k) = -SOC_N^k \cdot CAP_{\text{BP}} \cdot \bar{p}$. In this equation, $\bar{p}$ denotes the average price at which the energy could be sold. Subsequently, proceeding backwards in time, the cost g_{N-1}^k leading to the total cost $J(SOC_{N-1}^k)$ for every k is calculated. The transition between $N-1$ and N leading to the lowest total cost for each k then yields the desired $P_{N-1}^k = \mu_{N-1}^k(SOC_{N-1}^k)$. If the final state SOC_N is fixed to $SOC_N = SOC_{\text{fin}}$ or constrained by $SOC_N \geq SOC_{\text{fin}}$, this needs to be considered accordingly. Continuing this procedure up to the first time step $i = 0$, this leads to the minimized cost $J_{\gamma^k*}^k(SOC_0^k)$ and an optimal control policy $\gamma^k* = \{\mu_0^k*, ..., \mu_{N-1}^k*\}$ for every k corresponding to SOC_0^k. Since the initial SOC_0 is given, k corresponding to this value is chosen in order to identify the applicable control policy. Presuming deterministic prices, this approach can be proven to find a global optimum for the described problem [33].

In real-time operation the time progresses with new price information becoming available at each time step. Therefore, at each time-step a re-optimization considering the new set of price data is conducted.

III. Case Study

The presented method is applied to real-world data provided by four different energy market operators. The study gives an insight into the profitability of these markets regarding energy arbitrage using batteries such as stationary residential batteries or PEV batteries under various scenarios. The investigation further illustrates the role of battery degradation consideration, electricity price forecasts, and the impact of cost savings due to decreasing battery prices.

A. Market Description

The markets under consideration are the IESO[1] (Ontario), the NYISO[2] (New York), the NEMS[3] (Singapore), and the PJM[4] (eastern area of the United States). The relevant characteristics of the investigated markets are very similar. There are sub-markets trading energy as well as sub-markets where capacity is traded (*ancillary services*). Trade may happen in real-time as implemented in all four markets or additionally in a day-ahead manner as in NYISO and PJM. This study builds on *locational marginal prices* (LMP) from real-time markets which are computed for distinct nodes or zones based on current and projected capacity utilization. Time resolutions of LMPs are 5 min (IESO, NYISO, PJM) and 30 min (NEMS). Prices result from a clearing process ensuring that the lowest bids get dispatched first. All market operators also provide aggregated prices with time resolutions of one hour (apart from NEMS) and a coarser spatial resolution. These prices are typically used as wholesale prices paid by non-contestable consumers in the entire market area. This study uses the aggregation level of wholesale prices with exception of the NYISO where zonal and nodal prices are also considered. All data is publicly available on the operators' websites.

B. Data and Parameters

The price data covers real-time market prices for the years 2008 - 2015. Prices have an hourly resolution with exception of the NEMS prices which are provided in 30 min intervals. Prices considered in Section III-C1 and III-C2 are wholesale prices meaning that one price uniformly applies to the entire market area in a specific time period. In Section III-C3, the NYISO is investigated at a higher spatial and temporal resolution of the price data. The used data includes zonal prices representing sub-regions of the market as well as nodal prices for 508 generators. Furthermore, the implications of a time resolution of 5 min are investigated. Lookaheads of 1, 6, and 12 periods are considered. The first case represents a myopic agent which only considers information on the next time period while the other two cases represent non-myopic strategies. As in this investigation perfect forecasts based on cleared prices are assumed, profits subject to forecast uncertainty would lie between the myopic and the non-myopic outcome. For the battery costs, scenarios of US$ 0, US$ 150, and US$ 300 per kWh are investigated[5]. The zero battery cost scenario serves as a baseline illustrating the implications of not explicitly considering degradation costs for scheduling. According to [1], US$ 150 per kWh is considered a break even cost at which PEVs are expected to become a competitive mass market product. The same source considers the price of US$ 300 as a realistic number which can currently be achieved for PEV and home batteries. A battery capacity of 20 kWh is chosen which corresponds to a typical mid-class PEV such as the Nissan Leaf (24 kWh) or Mitsubishi i-MiEV (16 kWh). The C-rate is limited to 1 C, the combined efficiency of a charge-discharge process is set to $\eta = 0.8$, and cap_{EOL} is chosen to be 0.8. The SOC discretization required by the dynamic programming approach is set to 0.01 which is a sufficiently good compromise between accuracy and performance.

[1]http://www.ieso.ca
[2]http://www.nyiso.com
[3]https://www.emcsg.com
[4]http://www.pjm.com
[5]All prices are converted to US$ (S$ 1→US$ 0.72; C$ 1→US$ 0.74).

C. Results

The results show the influence of battery costs, the role of price forecasts, as well as the temporal and spatial variation of attainable profits. In Section III-C1 and III-C2 the influence of battery costs and lookahead are explored. The investigations on the influence of different spatial and temporal resolutions shown in Section III-C3 are based on a battery price of US$ 300 per kWh and a lookahead of 6.

1) Battery Costs: Fig. 1a shows average annual profits in the real-time market attainable by a myopic agent. The leftmost set of bars shows the case resulting from a scheduling approach not considering battery degradation. Profits range from US$ 340 (IESO, NEMS) to US$ 570 (NYISO). While these numbers do not consider battery costs, battery degradation according to (9) was internally tracked. Under the obtained cycling regime, the capacity of a newly purchased battery would, on average, have decreased to a factor of 0.66 - 0.79 of its initial value at the end of each year. Taking the EOL criterion $cap_{\mathrm{EOL}} = 0.8$ for PEVs, this would result in 1 - 2 battery replacements per year which is in line with the findings in [16] and [17]. This is because the lack of battery cost consideration during schedule optimization leads to large SOC swings and extreme SOC states resulting in fast capacity fade.

The central and rightmost sets of bars show the scenarios where the battery degradation model is included in the optimization. For a battery price of US$ 150 per kWh and a lookahead of 1, average annual profits range from US$ 30 (IESO, PJM) to US$ 100 (NEMS). While these numbers are considerably lower than in the previously described case, they indicate real profits with battery degradation being factored in. Capacities in these cases only decrease to 0.97 - 0.98 of their initial values over the course of a year. The degradation model thus ensures that energy is only cycled under conditions where revenues exceed degradation costs. With battery prices of US$ 300 per kWh, profits decrease to US$ 10 (IESO, PJM) to US$ 60 (NEMS). Capacity losses further decrease to 0.98 - 0.99, indicating that in these cases only small amounts of energy are cycled.

2) Role of Lookahead: As shown in Fig. 1b and 1c, profits can be increased by taking into account price forecasts. The smallest benefit of price forecasting is observed in the case without consideration of battery costs as shown by comparing the leftmost sets of bars in Fig. 1a and 1b/1c. In absence of battery costs, the system typically performs full cycles in any profitable period without planning for the next upcoming

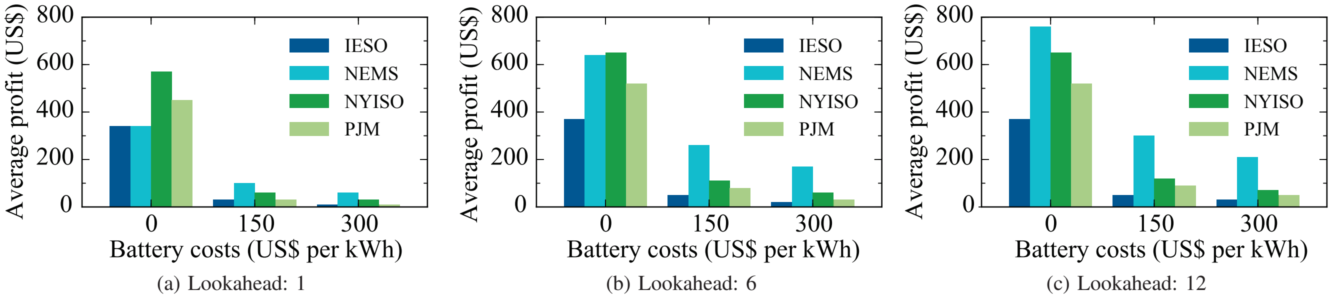

Figure 1: Average annual profits in different markets for different battery costs and lookaheads.

periods. The small difference between the scenarios with lookaheads of 1 and 6 or 12 stems from the fact that in some cases it might be worthwhile to abstain from cycling energy in one period because achievable profits are considerably higher in the following one. The relevance of forecasting data increases with battery price, so that profits increase by an average factor of 2 (2.5) for battery costs of US$ 150 (300) per kWh. This is because higher degradation costs result in a greater need to operate the battery in an SOC range in which degradation is small. This is facilitated by greater planning horizons. Increasing the lookahead from 6 to 12 only exhibits a moderate effect, meaning that a long forecasting horizon is not necessary for achieving near-optimal results.

3) Spatial and Temporal Variation: The importance of choosing appropriate locations for storage integration is investigated by computing profits in the different load zones of the NYISO for the years 2008 - 2015 with a battery price of US$ 300 per kWh and a lookahead of 6. The results listed in Table I show that the zonal profits averaged over these years range from US$ 70 (zone name: Genesee) to US$ 180 (Long Island). In the most profitable year 2013, profits exceed US$ 300 (Long Island). Averaging over the means of all zones yields profits of US$ 100 which is still notably higher than the profit of US$ 60 based on wholesale prices computed in Section III-C1. The influence of the location becomes even more eminent when considering prices at a nodal instead of a zonal level. Computations for 508 generator nodes for the year 2015 yield profits ranging from US$ 15 (node name: *Kintigh*) to US$ 450 (*Huntley67* and *Huntley68*). The implication of price data at a higher temporal resolution is investigated using zonal prices in intervals of 5 min. Averaging these prices over all zones while maintaining the 5 min resolution leads to a profit of US$ 300 for the year 2015. This is 5 times higher than the profits resulting from an hourly resolution of price data. The results show that given current battery costs and lifetimes, geographic location and temporal resolution of price data play a major role regarding profitable operation.

Table I: Profits in the different NYISO zones for the years 2008 to 2015.

	Profits (US$)			
Zone	Annual avg	σ	Min	Max
Capital	80	50	30	180
Central	80	50	30	200
Dunwoodie	110	50	40	180
Genesee	70	50	20	190
Hudson Valley	100	40	40	160
Long Island	180	60	120	310
Mohawk Valley	80	50	30	200
Millwood	110	40	40	180
New York City	110	40	50	190
North	80	70	30	230
West	90	60	30	180

IV. Conclusion and Outlook

The presented framework allows the automatized systematic investigation of energy arbitrage in real-time markets under consideration of price forecasts and, most importantly, battery degradation costs. The results show that arbitrage profits in all markets are generally very moderate and therefore do not entirely refute the profitability concerns referenced in Section I. The computations, however, show that appropriate consideration of battery degradation as part of the scheduling algorithm can in fact lead to moderately profitable outcome. A smaller but still important role is played by price forecasts which in the investigated cases could increase profits by an average factor of 2.5. As can be expected, any kind of price averaging either temporally or spatially has an adverse effect on profitability. The results at the example of the NYISO show that considering nodal prices can increase profits by a factor of up to 5 as compared to a uniform market price.

These results illustrate the shortfalls of too generalized profitability conclusions. In the most general cases, attainable profits may not provide a sufficiently large incentive for installing battery capacity for the primary purpose of energy arbitrage. For owners of PEVs or residential batteries buffering generation from photovoltaics, arbitrage may, however, contribute to faster amortization of their investment. Profitability can be tweaked by appropriately considering the particular market conditions including the temporal resolution of prices and by choosing parts of the grid with prevailing higher prices. This may be a reasonable starting point for niche applications of small-scale storage until battery prices have fallen to a sufficiently low level for location-independent mass deployment. Additional profits could be attained from providing ancillary services which will be investigated in future studies. Advantages in this case stem from the fact that most markets reward capacity provision in addition to energy dispatch, thus resulting in revenues without incurring degradation costs. Any of these implementations, however, require appropriate schemes for battery owners to participate in real-time and day-ahead markets. For commonly discussed approaches such as the involvement of an *aggregator*, sufficiently high margins to cover the additional costs for this entity need to be considered in the cost assessment.

While it was shown that price forecasts can increase profitability, these results are built on the assumption of perfect forecasts. Even though forecasting information with a time horizon of several hours is fairly accurate, the assumption of a perfect forecast still represents a best case. This will be further investigated by analyzing the effect of noise on forecast data as well as by collecting real-time price forecasts. Another aspect which will be subject to future work is the consideration of calendar aging in the battery degradation model. While this aging process can be assumed to be of much lower relevance than cycle aging, its consideration may still lead to an increase of degradation costs. With regard to battery costs, alternative potentially cheaper battery technologies as well as second-life applications for PEV batteries will also be considered.

References

[1] B. Nykvist and M. Nilsson, "Rapidly falling costs of battery packs for electric vehicles," *Nature Climate Change*, vol. 5, no. 4, pp. 329–332, 2015.

[2] D. Ciechanowicz, A. Knoll, P. Osswald, and D. Pelzer, *Towards a Business Case for Vehicle-to-Grid - Maximizing Profits in Ancillary Service Markets*. Springer, 2015, pp. 203–231.

[3] W. Kempton and J. Tomić, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *J. Power Sources*, vol. 144, no. 1, pp. 280–294, Jun. 2005.

[4] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of vehicle-to-grid on the distribution grid," *Electric Power Syst. Res.*, vol. 81, no. 1, pp. 185–192, Jan. 2011.

[5] J. Tomić and W. Kempton, "Using fleets of electric-drive vehicles for grid support," *J. Power Sources*, vol. 168, no. 2, pp. 459–468, Jun. 2007.

[6] S. B. Peterson, J. F. Whitacre, and J. Apt, "The economics of using plug-in hybrid electric vehicle battery packs for grid storage," *J. Power Sources*, vol. 195, no. 8, pp. 2377–2384, 2010.

[7] A. Bhatti, Z. Salam, M. Aziz, K. Yee, and R. Ashique, "Electric vehicles charging using photovoltaic: Status and technological review," *Renewable and Sustainable Energy Rev.s*, vol. 54, pp. 34–47, 2016.

[8] D. Richardson, "Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration," *Renewable and Sustainable Energy Rev.s*, vol. 19, pp. 247–254, 2013.

[9] J. C. Mukherjee and A. Gupta, "A review of charge scheduling of electric vehicles in smart grid," *IEEE Syst. J.*, vol. 9, no. 4, pp. 1541–1553, Dec 2015.

[10] F. Mwasilu, J. Justo, E.-K. Kim, T. Do, and J.-W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration," *Renewable and Sustainable Energy Rev.s*, vol. 34, pp. 501–516, 2014.

[11] A. Schuller, B. Dietz, C. Flath, and C. Weinhardt, "Charging strategies for battery electric vehicles: Economic benchmark and V2G potential," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2014–2222, 2014.

[12] D. Pelzer, D. Ciechanowicz, H. Aydt, and A. Knoll, "A price-responsive dispatching strategy for vehicle-to-grid: An economic evaluation applied to the case of Singapore," *J. Power Sources*, vol. 256, no. 0, pp. 345 – 353, 2014.

[13] S.-L. Andersson, A. Elofsson, M. Galus, L. Göransson, S. Karlsson, F. Johnsson, and G. Andersson, "Plug-in hybrid electric vehicles as regulating power providers: Case studies of Sweden and Germany," *Energy Policy*, vol. 38, no. 6, pp. 2751–2762, Jun. 2010.

[14] B. Lunz, Z. Yan, J. Gerschler, and D. Sauer, "Influence of plug-in hybrid electric vehicle charging strategies on charging and battery degradation costs," *Energy Policy*, vol. 46, pp. 511–519, 2012.

[15] C. Guenther, B. Schott, W. Hennings, P. Waldowski, and M. Danzer, "Model-based investigation of electric vehicle battery aging by means of vehicle-to-grid scenario simulations," *J. Power Sources*, vol. 239, pp. 604–610, 2013.

[16] J. Bishop, C. Axon, D. Bonilla, M. Tran, D. Banister, and M. McCulloch, "Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV," *Appl. Energy*, vol. 111, pp. 206–218, 2013.

[17] J. Bishop, C. Axon, D. Bonilla, and D. Banister, "Estimating the grid payments necessary to compensate additional costs to prospective electric vehicle owners who provide vehicle-to-grid ancillary services," *Energy*, vol. 94, pp. 715–727, 2016.

[18] R. Dufo-López, "Optimisation of size and control of grid-connected storage under real time electricity pricing conditions," *Appl. Energy*, vol. 140, pp. 395–408, 2015.

[19] A. Shcherbakova, A. Kleit, and J. Cho, "The value of energy storage in south korea's electricity market: A hotelling approach," *Appl. Energy*, vol. 125, pp. 93–102, 2014.

[20] E. L. Karfopoulos and N. D. Hatziargyriou, "Distributed coordination of electric vehicles providing v2g services," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 329–338, Jan 2016.

[21] E. Iversen, J. Morales, and H. Madsen, "Optimal charging of an electric vehicle using a markov decision process," *Appl. Energy*, vol. 123, pp. 1–12, 2014.

[22] A. Hoke, A. Brissette, D. Maksimovic, D. Kelly, A. Pratt, and D. Boundy, "Maximizing lithium ion vehicle battery life through optimized partial charging," in *IEEE PES Innovative Smart Grid Technol. (ISGT)*, Feb 2013, pp. 1–5.

[23] Z. Ma, S. Zou, and X. Liu, "A distributed charging coordination for large-scale plug-in electric vehicles considering battery degradation cost," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 5, pp. 2044–2052, Sept 2015.

[24] A. E. Trippe, R. Arunachala, T. Massier, A. Jossen, and T. Hamacher, "Charging optimization of battery electric vehicles including cycle battery aging," in *IEEE PES Innovative Smart Grid Technol. (ISGT)*, Oct 2014, pp. 1–6.

[25] M. Honarmand, A. Zakariazadeh, and S. Jadid, "Optimal scheduling of electric vehicles in an intelligent parking lot considering vehicle-to-grid concept and battery condition," *Energy*, vol. 65, pp. 572–579, 2014.

[26] X. Tan, Y. Wu, and D. H. K. Tsang, "A stochastic shortest path framework for quantifying the value and lifetime of battery energy storage under dynamic pricing," *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–1, 2016.

[27] T. A. Nguyen and M. L. Crow, "Stochastic optimization of renewable-based microgrid operation incorporating battery operating cost," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2289–2296, May 2016.

[28] G. He, Q. Chen, C. Kang, P. Pinson, and Q. Xia, "Optimal bidding strategy of battery storage in power markets considering performance-based regulation and battery cycle life," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2359–2367, Sept 2016.

[29] A. Hoke, A. Brissette, K. Smith, A. Pratt, and D. Maksimovic, "Accounting for lithium-ion battery degradation in electric vehicle charging optimization," *IEEE J. Emerging and Select. Topics in Power Electron.*, vol. 2, no. 3, pp. 691–700, Sept 2014.

[30] A. Marongiu, M. Roscher, and D. Sauer, "Influence of the vehicle-to-grid strategy on the aging behavior of lithium battery electric vehicles," *Appl. Energy*, vol. 137, pp. 899–912, 2015.

[31] M. Ecker, N. Nieto, S. Käbitz, J. Schmalstieg, H. Blanke, A. Warnecke, and D. Sauer, "Calendar and cycle life study of Li(NiMnCo)O2-based 18650 lithium-ion batteries," *J. Power Sources*, vol. 248, pp. 839–851, 2014.

[32] J. Schmalstieg, S. Käbitz, M. Ecker, and D. U. Sauer, "A holistic aging model for Li(NiMnCo)O2 based 18650 lithium-ion batteries," *J. Power Sources*, vol. 257, no. 0, pp. 325 – 334, 2014.

[33] D. P. Bertsekas, *Dynamic programming and optimal control*, 4th ed. Belmont, Mass.: Athena Scientific, 2012.