Joint optimisation of arbitrage profits and battery life degradation for grid storage application of battery electric vehicles

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Abstract. To meet European decarbonisation targets by 2050, the electrification of the transport sector is mandatory. Most electric vehicles rely on lithium-ion batteries, because they have a higher energy/power density and longer life span compared to other practical batteries such as zinc-carbon batteries. Electric vehicles can thus provide energy storage to support the system integration of generation from highly variable renewable sources, such as wind and photovoltaics (PV). However, charging/discharging causes batteries to degrade progressively with reduced capacity.

In this study, we investigate the impact of the joint optimisation of arbitrage revenue and battery degradation of electric vehicle batteries in a simplified setting, where historical prices allow for market participation of battery electric vehicle owners.

It is shown that the joint optimisation of both leads to stronger gains then the sum of both optimisation strategies and that including battery degradation into the model avoids state of charges close to the maximum at times. It can be concluded that degradation is an important aspect to consider in power system models, which incorporate any kind of lithium-ion battery storage.

1. Introduction

European power systems are transforming. Changes towards renewable generation are driven by aims of decarbonisation and sustainability. However, wind and solar power have intermittent generation profiles, which makes their power system integration challenging [1, 2]. Various options have been proposed in the past as contributions to the balance of generation and demand in the system: Optimising the mix of generation from different renewable power sources such as wind, solar or hydro power [3, 4, 5, 6, 7, 8], storage [9, 10, 11], transmission grid extensions [12, 13], or concentrated solar power imports from North Africa, which are attractive because of the ability to store energy in form of heat [14]. Other options include system-friendly renewables or load shifting [15, 16, 17, 18, 19].

As electric cars are getting more and more adequate for daily use due to significant cost reduction and driving range extension, the deployment of electric vehicles in the EU is gaining momentum [20]. Automotive companies like Daimler expect up to one in four cars sold to be electric by 2025 [21]. This process comes with a major opportunity: Electric vehicles are equipped with batteries, which therefore hold aggregated large amounts of energy capacity storage. Two
\(b(t)\) charging rate of battery
\(\hat{b}(t)\) charging capacity of battery
\(\tilde{b}(t)\) charging due to driving
\(\lambda_L\) price for degradation, i.e., relative share of investment cost
\(\lambda(t)\) time series of prices
\(L(t)\) life status of battery
\(\Delta L\) battery degradation relative to new battery
\(L_{cal}\) life status or aging due to calendaric processes
\(L_{cyc}\) life status or aging due to cycling processes
\(l_c\) aging of a single cycle
\(\sigma\) state of charge
\(\sigma_0\) reference state of charge
\(\sigma^+\) battery energy capacity
\(\delta\) depth of discharge
\(S\) stress factor
\(k\) constant of stress factor model
\(t\) time index
\(\bar{T}\) average temperature

Table 1: Important terminology

different options are exploitable for electric vehicles to balance power systems [22]: grid to vehicle (G2V) operation, i.e., adapting charging patterns to the generation side and vehicle to grid (V2G) operation, i.e., feeding electricity back into the grid. This sector coupling (usually, the heating sector is considered as well) is often expected to be a key ingredient to a decarbonised energy system. The coupling of the sectors electricity, heat and transport was investigated on the European scale in [23, 24] and found to provide significant cost reduction potential.

In this paper, the interaction of the battery electric vehicle and the electricity grid is investigated. It is assumed that a battery is discharged due to driving (based on an averaged demand profile) and can charge/discharge at hourly prices. The comparison of different charging strategies, e.g., with and without taking degradation into account, allows to study the relevance of degradation for batteries participating in energy markets. Furthermore, results indicate that the benefit of jointly optimising arbitrage and degradation leads to stronger benefits than the sum of both independently. The nomenclature used throughout this paper is shown in Table 1.

2. Methodology
To calculate discharging of batteries due to regular operation, i.e., driving and parking, we use traffic data that is provided by the Bundesanstalt für Straßenwesen (BAST) [25] and consists of hourly measurements for the year 2015 of approximately 1700 stations distributed along the German road network. First, this data is further simplified to obtain an averaged weekly demand profile. This weekly demand profiles as used in the following calculations can be seen in Fig. 1. In principle, it would be possible to take the data directly without averaging it further. However, to increase comparability with other works, which often rely on weekly profiles (e.g., [26]), we have adopted our data in an appropriate way. For prices, we use three years of historical EEX price data (2012-2015) [27]. This dataset consists of hourly day-ahead spot prices. A battery owner is assumed to be able to trade at hour \(t\) at corresponding price \(\lambda(t)\).
3. Battery life degradation

Lithium-ion battery aging is a complex process [28] that is not fully understood on the microscopic level. Processes involved include, for instance, solid-electrolyte interphase film formation [29, 30]. Caused by the lack of understanding degradation processes, battery lifetime predictions are usually based on empirical models rather than bottom-up mathematical modelling.

The degradation model used in this work is adapted from the work by Millner [31] and was further refined by Xu et al. [32].

The state of a battery is characterised by the parameter \( L \), where \( L = 0 \) refers to a new battery and \( \Delta L = 1 - L(t) \) describes the remaining energy capacity. Battery aging in a temporal interval from \( t_0 \) to \( t_1 \) is assumed to consist of cycle and calendar aging,

\[
L([t_0, t_1]) = L_{\text{cal}}([t_0, t_1]) + L_{\text{cyc}}([t_0, t_1]).
\]

Calendar aging is a function of the state of charge (SOC) \( \sigma \), \( L_{\text{cal}} = L_{\text{cal}}([t_0, t_1], \sigma, \bar{T}) \), and cycle aging the sum over aging caused by the \( n \) single cycles within the interval,

\[
L_{\text{cyc}} = \sum_{i=1}^{n} n_i l_c(\sigma_i, \delta_i, T_i).
\]

\( n_i \in \{0.5, 1.0\} \) indicates half (0.5) or full cycles (1.0). It is furthermore assumed, that aging processes can be expressed via a product of different stress factors. In the case of cycle aging this reads

\[
l_c(\delta, \sigma, T) = S_\delta(\delta)S_\sigma(\sigma)S_T(T),
\]

and in the case of calendar aging

\[
L_{\text{cal}}([t_0, t_1], \sigma, \bar{T}) = S_t([t_0, t_1])S_\sigma(\sigma)S_T(T).
\]

The stress factors of aging due to temperature, \( S_T \), and of aging due to passing of time, \( S_t \), are not considered here in an explicit way, because we focus on investigating the main behaviour.
of different optimisation strategies. However, if realistic values of degradation ought to be computed, these need to be taken into account, as well.

For the state of charge stress model, we adapt the exponential approach from Millner ([31]),

$$S_\sigma = e^{k_1(\sigma-\sigma_0)},$$

(5)

where $\sigma_0$ is a reference state of chart, chosen in this work to be 0.5 and $k_1$ a constant factor, which can be determined experimentally. For the depth of discharge stress model, different approaches can be found in literature. Besides the quadratic one,

$$S_\delta(\delta) = k_2\delta^2$$

(6)

that is adapted in this work, exponential and modified quadratic versions exist [32, 33]. The best fitting model depends on the battery chemistry. However, they all exhibit very similar behaviour [32].

To measure irregular charging cycles, the rainflow-cycle counting algorithm [34, 35] as proposed by Xu et al. [32] is used. It can be summarised for a time series as follows:

1. identify local maxima and minima
2. find global maximum and minimum (count as half-cycle)
3. wlog: if global maximum first (in the case of global minimum first, act vice versa):
   - 1. count half cycles from the global maximum to the most negative minimum before it, then the most positive maximum, etc.
   - 2. count half cycles after the global minimum until the most positive maximum, etc.
   - 3. identify all remaining as full cycles

Other degradation models are often simplified to linear or quadratic relationships [26, 36, 37]. This is strongly motivated by the fact that power system optimisation is often performed using linear models.

4. Results

The potential benefits of different optimisation schemes with different objectives are investigated. The benchmark is regular operation, i.e., cars are charged once they are below a certain threshold, which is chosen to be 0.8. 0.8 is a good tradeoff between fully charging the battery and hence exposing it to significant SOC stress and keeping at the same time a relatively high amount of energy at storage. If their charging level without grid interaction, $\tilde{\sigma}(t) = \sigma(t-1) + b_{\text{discharge}}(t)$, where $b_{\text{discharge}}$ is the discharge due to driving, falls below this level, the battery is charged,

$$b(t) = \min\{\hat{b}, 0.8 - \tilde{\sigma}(t)\},$$

(7)

where $\hat{b}$ is the charging capacity. If $b(t) - b_{\text{discharge}}(t) < 0$, the battery feeds electricity into the grid. It is assumed that cars can charge at all times. However, since we consider an average car battery (e.g., via averaging demand of cars), this seems an appropriate simplification. The overall cost is composed from the cost of charging and battery degradation,

$$\text{Cost} = \sum_t b(t) \cdot \lambda(t) + \Delta L \cdot \lambda_L.$$  

The first strategy aims at maximising arbitrage revenue via the injection $b(t)$ and reads

$$\begin{align*}
\text{minimise} & \quad \lambda(t)b(t) \\
\text{subject to} & \quad 0 \leq \sigma(t) \leq \sigma^+ \\
& \quad |b(t)| \leq 0.15\sigma^+, 
\end{align*}$$  

(9)
where $\lambda(t)$ is the price time series taken from historical spot price data for Germany. The charging strategy is always optimised under the assumption of perfect foresight for 72 hours, consecutively for the next 72 hours, etc. Furthermore, at the beginning/end of every cycle, state of charge is constrained to 0.5. In addition, we assume the reference state of charge to be 0.5 (as recommended by Xu et al. [32]) and put limits on the charging/discharging of 15% of the energy capacity. The second strategy simply aims at reducing overall battery degradation. It reads

$$\min_{b(t), t \in [t_0, t_0 + 72h]} \lambda_L \Delta L$$

subject to

$$0 \leq \sigma(t) \leq \sigma^+$$

$$|b(t)| \leq 0.15\sigma^+.$$ (10)

The final strategy combines both strategies by jointly maximising arbitrage revenue and minimising battery degradation:

$$\min_{b(t), t \in [t_0, t_0 + 72h]} \sum_t \lambda(t)b(t) + \lambda_L \Delta L$$

subject to

$$0 \leq \sigma(t) \leq \sigma^+$$

$$|b(t)| \leq 0.15\sigma^+.$$ (11)

We assume that all batteries charge/discharge following the same patterns. This can be shown to be the Nash-Equilibrium.

Figure 2 shows state of charge (a), charging rates (b) as well as the corresponding time series of prices (c) for two optimisation strategies in an arbitrary 72-hour period. Discharging due to regular operation was removed from the charging rates. In general, three price peaks and valleys can be observed with the first two being especially prominent with prices reaching values above 50 Euros / MWh, thus leading to peak-valley differences of 30 Euros / MWh and more. The last peak is less pronounced with a peak-valley difference of just around 10 Euro / MWh. The state of charge is shown for charging strategies three (maximising arbitrage revenue) and four (maximising arbitrage revenue under consideration of degradation) for the same period. It can be seen that taking degradation into account has the largest effect on the charging behaviour during the third peak-valley period, where price spreads are comparably small. In this case, not the full battery capacity is exploited. Instead, state of charge remains below the minimum, therefore reducing stress factors due to state of charge and depth of discharge.

The cost results averaged over the entire three years are depicted in Fig. 3. The case without optimisation works as the benchmark. If solely degradation is minimised, a cost reduction of 8% can be observed. This is reasonable, although it is a simple task to construct a price time series which would lead to a cost increase, if degradation was minimised without considering prices. Maximising arbitrage revenue without considering battery degradation leads to a cost reduction of approximately 19%. If both are jointly optimised, the resulting cost reduction equals approximately 38%. Therefore, the reduction by joint optimisation outperforms the sum of cost reductions by optimisation of the single terms. A similar result was found by Shi et al. in the case of peak shaving and arbitrage revenue maximisation and coined “super linear gain”[38].

5. Critical appraisal

Several simple assumptions were made within this work, which could be replaced in future work to yield results closer to reality. In the future, price signal statistics are expected to change due to quickly rising shares of renewables and their intermittent feed-in profiles as well as increased flexibility of the demand side due to price signals reaching consumers. Hence, it seems reasonable
Figure 2: All time series show the same exemplary time period of 72 consecutive hours in hourly resolution. Discharging due to driving was subtracted from the charging rate in Fig. b).

Figure 3: Cost of charging and degradation minus arbitrage revenue from market participation for the different charging strategies.

to study the potential gains of market participation of electric vehicle battery owners in a highly renewable power system, where prices can be obtained using shadow prices in an investment
optimisation program. Furthermore, the battery chemistry was not specified further, besides the assumption of the quadratic model for depth of discharge degradation. Specifying the battery chemistry could allow for realistic numbers on prices and degradation constants and consequently statements on future real-live operation and its cost performance. Several heuristic assumption on the charging level were made. These include, for example, that the SOC at the beginning and end of each period is constrained to 0.5. Investigating the sensitivity of the results to the choice of this and other heuristic parameter is planned as a future extension of this work.

6. Summary, conclusion and outlook
In this work, the joint optimisation of arbitrage revenue and battery degradation was investigated in a simplified setting. It was shown that it leads to higher gain than the sum of the optimisation of the two processes separately. The minimisation of degradation alone without consideration of variable prices leads to a reduction of approximately 8% in overall cost. In principle, one could easily construct a case where this strategy would increase overall cost. However, it seems that prices are sufficiently strong correlated to discharging processes and thus allow for a reduction by degradation minimisation alone.

Semi-empirical lithium-ion battery degradation models like the one used in this work show that degradation is smallest when the state of charge is close to average and deep discharges are avoided. These non-linearities make the integration into power system optimisation models, which are for obvious reasons commonly formulated in a linear way, difficult. However, since investment into battery electric vehicles happens independently of grid storage application, it seems reasonable to model their operation with endogenous prices as was done in this work. Another interesting question this research raises is that of the optimum sizing of batteries in electric vehicles. Typical combustion-based cars have gas tanks which might be equivalent to batteries with capacities of around 150 KWh. However, because degradation is reduced mostly close to the reference state of charge and deep discharge cycles should be avoided, it seems reasonable to expect optimum battery sizes to be larger than those values. Finally, the underlying research concludes that the electrification of the transport sector contributes in two ways to the success of the European energy transition: i) by decarbonisation of the transport sector, ii) by allocation of storage to integrate variable renewable generation.

Acknowledgments
I thank my colleagues from FIAS, especially Tom Brown, David Schlachtberger and Jonas Hoersch for helpful suggestions. Furthermore, I thank Bruno Schyska from the University of Oldenburg as well. Additional gratitudes go to two anonymous reviewers for helpful comments and constructive criticism. A. Kies is financially supported by Stiftung Polytechnische Gesellschaft Frankfurt am Main.

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