Reinforcement Learning Portfolio Optimization of Electric Vehicle Virtual Power Plants

Master Thesis

Author: Tobias Richter
Supervisor: Prof. Dr. Wolfgang Ketter

Department of Information Systems for Sustainable Society
Faculty of Management, Economics and Social Sciences
University of Cologne

October, 2018

Contents

1 Introduction (10%)

1.1 Research Motivation

- Lopes, Soares, and Almeida, 2011

1.2 Research Question

1.3 Relevance

2 Related Literature (10%)

2.1 Smart Charging and Balancing the Electric Grid with EV Fleets

The increasing penetration of EVs has a substantial effect on electricity consumption patterns. During charging periods, power flows and grid losses increase considerably and challenge the grid. Operators have to reinforce the grid to ensure that transformers and substations do not get overloaded (Lopes et al., 2011; Sioshansi, 2012). Loading multiple EVs in the same neighbourhood, or worse, whole EV fleets at once, stress the grid. In these cases, even brown- or blackouts are possible (Kim, Tabors, Stoddard, & Allmendinger, 2012). Despite these challenges, it is possible to postpone the physical reinforcement by adopting smart charging strategies. In smart charging, EVs get charged when the grid is less congested to achieve more grid stability. Smart charging reduces peaks in electricity demand, called *Peak Cutting* and complement the grid in times of low demand, called *Valley Filling*. Smart charging has been researched thoroughly in the IS literature.

Valogianni, Ketter, Collins, and Zhdanov (2014) find that using intelligent agents to schedule EV charging, substantially reshapes the energy demand and reduces peak demand without violating individual household preferences. Moreover, they show that the proposed smart charging behaviour reduced average energy prices and thus economically benefit households. In another study Kara et al. (2015) investigate the effect of smart charging on public charging stations in California. Controlling for arrival and departure times, the authors present beneficial results for the distribution system operator (DSO) and the owners of EVs. A price reduction in energy bills and a peak load reduction could be determined. An extension of the smart charging concept is Vehicle-to-Grid (V2G). When equipped with V2G devices, EVs can discharge their batteries back into the grid. Several authors conduct research on this technology in respect to grid stabilization effects and arbitrage possibilities. Schill (2011) find that EVs can be beneficial for average consumer electricity prices when the EVs can be used as storage. Excess EV battery capacity can be used to charge in off-peak hours and discharge in peak hours, when the prices are higher. These arbitrage possibilities, reverses welfare effects of generators and increases general overall welfare and consumer surplus. Tomić and Kempton (2007) show that the arbitrage opportunities are especially prominent when a high variability in electricity prices on the target electricity market exists. The authors state that short intervals between the contract of sale and the physical delivery of electricity increase arbitrage benefits. Consequently ancillary service markets, like frequency control and operating reserve markets are attractive for smart charging.

Peterson, Whitacre, and Apt (2010) investigate energy arbitrage profitability with V2G in the light of battery depreciation costs in the US. Their results indicate that large-scale use of EV batteries for grid storage does not yield enough profits to incentivize owners to participate in V2G activities. Considering battery depreciation cost they arrive at an annual profit of only 6$ - 72$ per EV. Brandt, Wagner, and Neumann (2017) evaluated a business model for parking garage operators operating on the German frequency regulation market. When taking infrastructure costs and battery depreciation costs into account they concluded that the proposed vehicle-grid integration is not profitable. Even with generous assumptions about EV adoption rates in Germany and altered auction mechanisms they arrived at negative profits. (Kahlen, Ketter, & Gupta, 2017) used EV fleets to offer balancing services to the grid. Evaluating the impact of V2G in their model the authors come to the conclusion that V2G would only be profitable if reserve power prices would be twice as high. Given the results from the aforementioned studies, we decided not to include V2G into our model, since expected profits are, at most, marginal.

To maximize profits, it is essential for market participants to develop good bidding strategies. Successful bidding strategies to jointly participate in multiple markets have been developed e.g. by Mashhour and Moghaddas-Tafreshi (2011). The authors use stationary battery storage to participate in the spinning reserve market and the day-ahead market at the same time. They developed a non-equilibrium model, which solves the presented mixed-integer program with Genetic Programming (GP). Contrarily, we use a model-free RL agent that learns an optimal policy (i.e. a trading strategy) from actions it takes in the environment (i.e. bidding on electricity markets). Using a model-free approach is especially beneficial for us, since additional unknown variables and constraints (i.e. customer mobility demand), makes it very hard to formulate a mathematical model.

Similar research to Mashhour and Moghaddas-Tafreshi (2011) has been done by He, Chen, Kang, Pinson, and Xia (2016). The authors additionally incorporate battery life cycle in their profit maximization model, which proves to be a decisive factor. In contrast to the authors, we jointly participated in the secondary operating reserve and spot market with the *non-stationary* storage of EV batteries. Because shared EVs have to satisfy mobility demands, they have to be charged nonetheless, which allows us to safely exclude battery deprecation from our model. Further, we chose the intraday continuous market over the day-ahead market, as it has the lowest reaction time of the spot markets, and thus potentially offers higher profits (Tomić & Kempton, 2007).

Previous studies often assume that car owners or households can directly trade on electricity markets. In reality, this is not possible due to minimum capacity requirements of the markets, that single EVs do not meet. For example, the German Control Reserve Market (GCRM) has a minimum trading capacity of 1MW to 5MW, depending on the specific market. In order to reach the minimum capacity, over 200 EVs would need to be connected to the grid via a normal 4.6kW charging station at the same time. Ketter, Collins, and Reddy (2013) introduced the notion of electricity brokers, aggregators that act on behalf of a group of individuals or households to participate in electricity markets. Brandt et al. (2017) and Kahlen, Ketter, and van Dalen (2014) successfully showed in their studies that electricity brokers can overcome the capacity issues by aggregating EV batteries. In addition to electricity brokers, we apply the concept of Virtual Power Plants (VPPs). VPPs are flexible portfolios of distributed energy resources, which are presented with a single load profile to the system operator, making them eligible for market participation and ancillary service provisioning (Pudjianto, Ramsay, & Strbac, 2007). Hence VPPs allow to provide aggregated regulation capacity to the market without knowing which exact sources provide the promised capacity until delivery time (Kahlen et al., 2017). This concept is specifically useful when dealing with EV fleets: VPPs enable carsharing providers to issue bids and asks based on an estimate of available fleet capacity, without knowing beforehand which exact EVs will provide the capacity at the time of delivery. Based on the battery charge and the availability EVs, an intelligent agent will decide in real-time which vehicles provide the capacity.

Carsharing providers manage large EV fleets, which makes it possible for them to use the presented concepts as a viable business extension. We look at free float carsharing, a popular concept where cars can be picked up and parked everywhere and billing is done by the minute. Free float carsharing offers more flexibility to its users, saves resources and reduces carbon emissions (Firnkorn & Müller, 2015). In most previous studies concerned with using EVs for electricity trading, it was assumed that trips are fixed and known in advance, e.g. in Tomić and Kempton (2007). The free float concept adds uncertainty and nondeterministic behavior, which make predictions about where and when a car will be rented out a complex issue.

Kahlen et al. (2017) showed that is possible to use free float carsharing fleets as VPPs to profitably offer balancing services to the grid. The authors compared cases from three different cities across Europe and the US. They used an event-based simulation, bootstrapped with real-world carsharing and secondary operating reserve market data from the respective cities, to arrive at their results. A central dilemma within this research is to decide whether an EV should be committed to being used as a VPP or to be free for rent, in the core a classification problem. Since rental profits are considerably higher than profits to be made from electricity trading, it is crucial to not allocate an EV to a VPP when it could have been rented out otherwise. To deal with the asymmetric payoff, Kahlen et al. use stratified sampling in their classifier. This method gives rental misclassifications higher weights, which reduces the likelihood of EVs to participate in VPP activities. The authors use a Random Forest regression model to predict the available balancing capacity to offer to the market. The predictions are done on an aggregated fleet level, in order to leverage risk-pooling effects. The decision which EVs will provide the regulation capacity is made at delivery time based on the likelihood that the vehicle is rented out and on the expected (predicted) benefits of the EV.

In a similar study the authors showed, that carsharing companies can participate in day-ahead markets for arbitrage purposes (Kahlen, Ketter, & van Dalen, 2018). In this paper the authors use a time-series model to predict available trading capacity, due to the closer time between commitment and delivery. Another central problem for carsharing provider is that committed trades which can't be fulfilled result in heavy penalties from the system operator or electricity exchange. In other words, it should be avoided at all costs, that the fleet commits to buy any amount of electricity, for which it does not have enough available EVs to charge it at delivery time. To address this issue, the authors develop a mean asymmetric weighted (MAW) objective function. They use it for their time-series based prediction model, to penalize committing an EV to VPP when it would have been rented out otherwise.

Because of the two issues mentioned above, Kahlen et al. (2018) can only make very conservative estimations and commitments of available overall capacity to be traded on the markets, which results in a high amount of foregone profits. This effect is especially prominent when participating on the secondary operating reserve market, since commitments have to be made one week in advance, where mobility demands are still uncertain. Kahlen et al. (2017) state that in 42% to 80% of the cases EVs are *not* committed to a VPP when it would have been profitable to do so.

We are proposing a solution, in which the EV fleet participates on the balancing market and intraday market simultaneously. With this approach we aim to align the potentially higher profits on the balancing markets, mentioned in Tomić and Kempton (2007) with the more accurate capacity estimations, which can be made on intraday markets (because time between commitment and delivery is smaller). We follow Kahlen et al. (2017) with this approach, who propose to work on a combination of multiple markets in the future.

2.2 Reinforcement Learning in Smart Grids

Previous research showed that intelligent agents equipped with Reinforcement Learning methods can successfully take action in the smart grid. Reddy and Veloso (2011a, 2011b) conducted research, in which autonomous broker agents (Ketter et al., 2013) learn their strategies using RL. Peters, Ketter, Saar-Tsechansky, and Collins (2013) build on that work and further enhance the method, by learning over larger state spaces to accommodate arbitrary economic signals. This is especially beneficial in smart markets, because the markets structures might change in the future and intelligent agents should adapt to a variety of market structures and conditions.

(Vázquez-Canteli & Nagy, 2019)

Valogianni et al. (2014) adopt RL methods to learn electricity consumption behavior of households. The authors implement these methods in intelligent agents to smart charge EVs more effectively. Vandael, Claessens, Ernst, Holvoet, and Deconinck (2015) use RL to learn collective EV fleet charging behavior to profitably purchase electricity on the day-ahead market. We consider RL a perfect fit for the design of our proposed intelligent agent, especially as a solution for our Research Question 2. When dynamically optimizing the VPP portfolio composition of the fleet, there is no historical data available to train a model. Using RL and a reward function that maximizes the overall profitability of the fleet, the agent can learn from its environment with unknown dynamics and take a certain set of actions. The agent can consider different states (e.g. current and forecasted rental demand levels and electricity prices) to take actions (e.g. allocate battery capacity to different types of VPPs) that maximizes the reward function.

3 Theoretical Background (10%)

3.1 Electricity Markets

3.1.1 Balancing Market

3.1.2 Spot Market

3.2 Reinforcement Learning

3.2.1 Notation

The input to the network $x \in \mathbb{R}^D$ is fed to the first residual layer to get the activation $y = x + \sigma(wx + b) \in \mathbb{R}^D$ with $w \in \mathbb{R}^{D \times D}$, and $b \in \mathbb{R}^D$ the weights and bias of the layer.

3.2.2 Markow Decision Processes

3.2.3 Q-Learning

3.2.4 Function Approximation

3.2.5 Exploitation-Exploration Tradeoff

3.2.6 Deep Reinforcement Learning

4 Empirical Setting / Data (10%)

4.1 Carsharing Fleets of Electric Vehicles

4.1.1 Raw Data

The dataset consists of 500 EVs in Stuttgart. As displayed in Table 1, the data contain spatio-temporal attributes, such as timestamp, coordinates, and address of the EVs. Additionally, status attributes of the interior and exterior are given, the relative state of charge and information whether the EV is plugged into one of the 200 charging stations in Stuttgart.

Table 1: Raw Car2Go Trip Data from Stuttgart

Number Plate	Latitude	Longitude	Street	Zip Code	Engine Typ
S-GO2471	9.19121	48.68895	Parkplatz Flughafen	70692	electric
S-GO2471	9.15922	48.78848	Salzmannweg 3	70192	electric
S-GO2471	9.17496	48.74928	Felix-Dahn-Str.45	70597	electric
S-GO2471	9.17496	48.74928	Felix-Dahn-Str.45	70597	electric
S-GO2471	9.17496	48.74928	Felix-Dahn-Str.45	70597	electric
Number Plate	Interior	Exterior	Timestamp	Charging	State of Char
S-GO2471	good	good	22.12.2017 20:10	no	94
S-GO2471	good	good	24.12.2017 23:05	no	72
S-GO2471	good	good	26.12.2017 00:40	yes	81
S-GO2471	good	good	26.12.2017 00:45	yes	83
S-GO2471	good	good	26.12.2017 00:50	yes	84

4.1.2 Preprocessing Steps

4.2 Electricity Markets Data

4.2.1 Secondary Operating Reserve Market

4.2.2 Intraday Continuous Spot Market

5 Model: FleetRL (20%)

5.1 Information Assumptions

5.2 Mobility Demand & Clearing Price Prediction

5.3 Reinforcement Learning Approach

5.4 Bidding Strategy

6 Evaluation (30%)

6.1 Event-based Simulation

6.2 Benchmark: Ad-hoc Strategies

6.3 FleetRL

6.4 Sensitivity Analysis: Prediction Accuracy

6.5 Sensitivity Analysis: Infrastructure Changes

6.6 Sensitivity Analysis: Bidding Strategy

7 Discussion (5%)

7.1 Generalizability

7.2 Future Electricity Landscape

7.3 Limitations

8 Conclusion (5%)

8.1 Contribution

8.2 Future Research

References

Brandt, T., Wagner, S., & Neumann, D. (2017). Evaluating a business model for vehicle-grid integration: Evidence from germany. *Transportation Research Part D: Transport and Environment*, 488–504. doi:10.1016/j.trd.2016.11.017

Firnkorn, J., & Müller, M. (2015). Free-floating electric carsharing-fleets in smart cities: The dawning of a post-private car era in urban environments? *Environmental Science & Policy*, 30–40. doi:10.1016/j.envsci.2014.09.005

He, G., Chen, Q., Kang, C., Pinson, P., & Xia, Q. (2016). Optimal bidding strategy of battery storage in power markets considering performance-based regulation and battery cycle life. *IEEE Transactions on Smart Grid*, 2359–2367. doi:10.1109/tsg.2015.2424314

Kahlen, M., Ketter, W., & Gupta, A. (2017). Fleetpower: Creating virtual power plants in sustainable smart electricity markets.

Kahlen, M., Ketter, W., & van Dalen, J. (2014). Balancing with electric vehicles: A profitable business model.

Kahlen, M., Ketter, W., & van Dalen, J. (2018). Electric vehicle virtual power plant dilemma: Grid balancing versus customer mobility. *Production and Operations Management.*

Kara, E. C., Macdonald, J. S., Black, D., Bérges, M., Hug, G., & Kiliccote, S. (2015). Estimating the benefits of electric vehicle smart charging at non-residential locations: A data-driven approach. *Applied Energy*, 515–525. doi:10.1016/j.apenergy.2015.05.072

Ketter, W., Collins, J., & Reddy, P. (2013). Power tac: A competitive economic simulation of the smart grid. *Energy Economics*, 262–270. doi:10.1016/j.eneco.2013.04.015

Kim, E. L., Tabors, R. D., Stoddard, R. B., & Allmendinger, T. E. (2012). Carbitrage: Utility integration of electric vehicles and the smart grid. *The Electricity Journal*, 16–23. doi:10.1016/j.tej.2012.02.002

Lopes, J. A. P., Soares, F. J., & Almeida, P. M. R. (2011). Integration of electric vehicles in the electric power system. *Proceedings of the IEEE*, 168–183. doi:10.1109/jproc.2010.2066250

Mashhour, E., & Moghaddas-Tafreshi, S. M. (2011). Bidding strategy of virtual power plant for participating in energy and spinning reserve markets-part II: Numerical analysis. *IEEE Transactions on Power Systems*, 957–964. doi:10.1109/tpwrs.2010.2070883

Peters, M., Ketter, W., Saar-Tsechansky, M., & Collins, J. (2013). A reinforcement learning approach to autonomous decision-making in smart electricity markets. *Machine learning*, 5–39.

Peterson, S. B., Whitacre, J., & Apt, J. (2010). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Journal of Power Sources*, 2377–2384. doi:10.1016/j.jpowsour.2009.09.070

Pudjianto, D., Ramsay, C., & Strbac, G. (2007). Virtual power plant and system integration of distributed energy resources. *IET Renewable Power Generation*, 10. doi:10.1049/iet-rpg:20060023

Reddy, P. P., & Veloso, M. M. (2011a). Learned behaviors of multiple autonomous agents in smart grid markets. In *Aaai*.

Reddy, P. P., & Veloso, M. M. (2011b). Strategy learning for autonomous agents in smart grid markets. In *Ijcai proceedings-international joint conference on artificial intelligence*.

Schill, W.-P. (2011). Electric vehicles in imperfect electricity markets: The case of germany. *Energy Policy*, 6178–6189. doi:10.1016/j.enpol.2011.07.018

Sioshansi, R. (2012). The impacts of electricity tariffs on plug-in hybrid electric vehicle charging, costs, and emissions. *Operations Research*, 506–516. doi:10.1287/opre.1120.1038

Tomić, J., & Kempton, W. (2007). Using fleets of electric-drive vehicles for grid support. *Journal of Power Sources*, 459–468. doi:10.1016/j.jpowsour.2007.03.010

Valogianni, K., Ketter, W., Collins, J., & Zhdanov, D. (2014). Effective management of electric vehicle storage using smart charging. In *Aaai* (pp. 472–478).

Vandael, S., Claessens, B., Ernst, D., Holvoet, T., & Deconinck, G. (2015). Reinforcement learning of heuristic ev fleet charging in a day-ahead electricity market. *IEEE Transactions on Smart Grid*, 1795–1805. doi:10.1109/tsg.2015.2393059

Vázquez-Canteli, J. R., & Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Applied Energy*, 1072–1089. doi:10.1016/j.apenergy.2018.11.002