Reinforcement Learning Portfolio Optimization of Electric Vehicle Virtual Power Plants

Master Thesis

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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 in order that transformers and substations don't get overloaded (Lopes et al., 2011). Loading multiple EVs in the same neighbourhood, or worse whole EV fleets at once, stress the grid. Kim, Tabors, Stoddard, and Allmendinger (2012) find that in these cases, even brown- or blackouts are possible. Despite these challenges, it is possible to postpone the physical reinforcement by adopting smart charging strategies (Kim et al., 2012). In smart charging, EVs get charged when the grid is less congested to achieve more grid stability. Smart charging reduces peaks in electricity demand ("Peak Cutting") and complement times of low demand ("Valley Filling").

Valogianni, Ketter, Collins, and Zhdanov (2014) find that using intelligent agents to facilitate smart charging, can substantially benefit households. Kara et al. (2015) present results, in which smart charging reduced electricity bills for users of public EV charging stations in California.

An extension of the smart charging concept is Vehicle-to-Grid (V2G). EVs equipped with V2G devices can discharge their batteries back into the grid. Schill (2011) find that EVs can be beneficial for consumer electricity prices when they are used as storage. Similar results were shown by Reichert (2010) and Peterson, Whitacre, and Apt (2010), they point out that battery technology and battery costs are a crucial factor for profitability. Tomić and Kempton (2007) show that V2G can profitable, especially when there is a high variability in electricity prices on the market. The authors state that shorter intervals between sale and physical delivery increase the benefits.

Successful trading strategies to jointly participate in multiple markets have been developed by Mashhour and Moghaddas-Tafreshi (2011). Using stationary storage the authors use VPPs to participate in the spinning reserve market and day-ahead market at the same time. Similar research has been done by He, Chen, Kang, Pinson, and Xia (2016). The authors take the battery life cycle into account, which proves to be a decisive factor. In contrast, we aim to jointly participate in the operating reserve and spot market with *non-stationary* storage, while considering the battery life cycle as well. Following the findings of Tomić and Kempton (2007), we choose the intraday continuous market over the day-ahead market, as it has the lowest reaction time of the spot markets.

Previous studies often make the assumption 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. For example, the German secondary reserve market has a 1 MW minimum trading capacity, while the maximum battery capacity of i.e. a *Smart ForTwo Electric* is 16.50 kWh.

Ketter, Collins, and Reddy (2013) introduced the notion of electricity brokers, intelligent agents that act on behalf of a group of individuals or households to participate on electricity markets. Brandt, Wagner, and Neumann (2017) and Kahlen, Ketter, and van Dalen (2014) successfully showed in simulations that electricity brokers can overcome the capacity issues by aggregating distributed electricity sources.

Carsharing providers which manage large EV fleets, can use their EVs as VPPs to participate on electricity markets. We look at the concept of free float carsharing, an approach which offers more flexibility to its users, saves resources and reduces carbon emissions (Firnkorn & Müller, 2015). In most previous studies concerning using EVs for electricity trading, it was assumed that trips are fixed and known in advance. The free float concept adds uncertainty and nondeterministic behavior, as cars can be picked up and parked everywhere and billing is done by the minute. This makes predictions about the where and when of a car rental a complex issue. Wagner, Brandt, and Neumann (2016) address this problem by taking Points of Interests from Google Maps as an additional predictor.

Kahlen, Ketter, and Gupta (2017), Tomić and Kempton (2007) showed that is possible to use free floating carsharing fleets as VPPs to profitably offer balancing services to the grid. The authors also showed that with a similar approach, carsharing companies can participate on day-ahead markets for arbitrage purposes (Kahlen, Ketter, & van Dalen, 2018). 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. Rental profits are considerably higher than profits to be made from electricity trading.

Another central problem is that offering capacity to the grid, which you can not provide, results in heavy penalties, which should be avoided at all costs. To address this issue, the authors make use of asymmetric objective functions that heavily penalize committing an EV to a VPP, when it would have been rented otherwise. Therefore only very conservative estimations and commitments of available overall capacity to be traded on the markets are made. This results in a high amount of foregone profits when bidding on the balancing market. Kahlen and Ketter (2015) state that in 42% to 80% of the time EVs are *not* committed to a VPP when it would have been profitable (i.e. the EV has not been rented out).

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 with the more accurate capacity estimations, which can be made on intraday markets (because time between commitment and delivery is smaller). We follow Kahlen and Ketter (2015) with this approach, who also propose a combination of multiple markets in future work on this topic.

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 (5%)

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

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Number Plate	Latitude	Longitude	Street	Zip Code	Engine Typ
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 Research Design/Method? (5%)

5.1 IS-Design Science Research

5.2 Event-based Simulation

6 Model: FleetRL (20%)

6.1 Mobility Demand & Clearing Price Prediction

6.2 Reinforcement Learning Approach

6.3 Bidding Strategy

7 Evaluation (20%)

7.1 Event-based Simulation

7.2 Benchmark: Ad-hoc Strategies

7.3 FleetRL

7.4 Sensitivity Analysis: Prediction Accuracy

7.5 Sensitivity Analysis: Infrastructure Changes

8 Discussion (5%)

8.1 Generalisability

8.2 Future Electricity Landscape

8.3 Limitations

9 Conclusion (5%)

9.1 Contribution

9.2 Future Research

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- See (Vázquez-Canteli & Nagy, 2019) conclusion for limitations in RL.