Learning Portfolio Optimization of Electric Vehicle Virtual Power Plants in Smart Sustainable Electricity Markets: A Reinforcement Learning Approach

Master Thesis Proposal

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

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1 Introduction

1.1 Research Motivation

The global climate change is one biggest challenges of our time. Carbon emissions need to be reduced and the shift to sustainable energy sources is inevitable. But integration of renewables into the electricity grid proves to be difficult: Solar and wind energy is intermittent and hard to integrate into the power grid. Sustainable electricity production is dependent on the weather; under- and oversupplies occur and destabilize the grid.

Virtual power plants (VPP) play an important role in stabilizing the grid. VPPs aggregate distributed power sources to consume and produce electricity when it is needed. Carsharing companies operate large, centrally managed fleets of electric vehicles (EV) in major cities around the world. These EV fleets can be turned into VPPs, using their batteries as combined electricity storage. In this way, EV fleets can offer balancing services to the power grid or trade electricity on the open markets for arbitrage purposes. Carsharing companies can charge the fleet (buy electricity), when there is an excess of electricity on the market and discharge EVs (sell electricity), when there is a shortage of electricity. By making EVs available to be used as a VPP, carsharing companies compromise customer mobility and the profitability of the fleet. Renting out an EV to a customer is considerably more lucrative than using it for trading electricity.

Knowing how many EVs will most likely be rented out in a future point of time and consequently obtaining an accurate forecast of available battery capacity is essential for a successful trading strategy. Moreover, it is possible for fleet owners to trade on multiple electricity markets simultaneously. Electricity markets differ in price elasticity, as well as reaction time between contractual agreement and physical delivery.

Participating in operating reserve markets and spot markets at the same time can mitigate risks and increase profits. Allocating EVs to different types of VPPs, that using a reinforcement learning approach.

In this research we propose a portfolio optimizing strategy, in which the best composition of the VPP portfolio, consisting of operating reserve VPPs and spot market VPPs, will be dynamically learned. To address changing electricity price levels and customer demands over time we additionally propose the use of an intelligent agent. The agent learns from historical data, its current environment and

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realized profits to adjust its trading strategy dynamically.

The following tasks will be performed by the agent in real time: 1) *Allocation of plugged in EVs to idle or VPP state*, 2) *Learn the optimal VPP portfolio composition* and 3) *Place bids and asks on corresponding electricity markets with an integrated trading strategy.*

1.2 Research Question

Drawing upon the research motivation, the following research questions are derived. They build upon another and will be sequentially addressed during this research:

1. *What are spatio-temporal customer demand patterns of carsharing EVs?*

   Knowing customer demand patterns results in an accurate forecast of how much available battery capacity an EV fleet will have at any point in time.

2. *What is the optimal allocation ratio of the available capacity between operating reserve market VPPs and spot market VPPs?*

   Dynamically learning the optimal share of capacity to trade on the respective markets will maximize profits while reducing the risk of foregone customer profits.

3. *How does an integrated bidding strategy look like, which considers trading electricity the secondary operating reserve market and the continuous intraday market simultaneously?*

   Designing a strategy and determine optimal auction prices, which takes the specific market designs into account.

2 Relevance of the Research

2.1 Relevance to Practice

From a business perspective, this research is relevant to carsharing companies operating an EV fleet, such as Car2Go or DriveNow. We will show how these companies can increase their profits, using idle EVs as VPPs to trade electricity on multiple markets simultaneously.

We propose the use of a decision support system (DSS), which allocates idle EVs to different types of VPPs or to be available for renting. Further, the DSS

will determine optimal capacity-price pairs to place ask and bid on the individual electricity markets.

Using an event-based simulation we will estimate the profitability increase, when implementing the proposed methods. This will be done using real-world data from German electricity markets and trip data from a German carsharing provider.

2.2 Relevance to Science

From a scientific perspective, this research is relevant to the stream of agent-based decision making in smart markets (Bichler, Gupta, & Ketter, 2010; Peters, Ketter, Saar-Tsechansky, & Collins, 2013). We will contribute to the body of Design Science in Information Systems (Hevner, March, Park, & Ram, 2004) and draw upon work, which has been done in multitude of research areas: Virtual Power Plants in smart electricity markets (Pudjianto, Ramsay, & Strbac, 2007), carsharing as a new way of sustainable mobility and advanced machine learning and AI methods for forecasting and prediction.

Similar research has been carried out by Kahlen, Ketter, and van Dalen (2018) and Kahlen, Ketter, and Gupta (2017). In their research, the authors concentrate on participating in one type of electricity market at a time. As proposed by Kahlen et al. we will take this research further and use the EV VPPs to act on multiple types of electricity markets simultaneously. Moreover, we aim to use sophisticated machine learning methods (i.e. reinforcement learning, neural networks, ensemble learning) to carry out more accurate forecasts of rental demand and dynamically learn allocation ratios to the individual markets.

He, Chen, Kang, Pinson, and Xia (2016) and Mashhour and Moghaddas-Tafreshi (2011a, 2011b) conducted research on optimal bidding strategies for using VPPs to jointly bid on multiple markets. The authors use stationary storage to participate in day-ahead and spinning-reserve markets. Contrarily, we aim to use non-stationary storage (i.e. EV batteries) to participate in the continuous intraday market and the secondary reserve market (known as real-time market in the US).

2.3 Relevance to Society

This research contributes to the overall welfare of society in three points. First, VPPs of EVs provide extra balancing services to the power grid. The VPPs can consume excess electricity almost instantly and stabilize the power grid. When integrating

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more intermittent renewable electricity sources into the grid in the future, such balancing services will become indispensable.

Second, a reduction of electricity prices for the end-consumer is expected. Integrating VPPs into the power grid increases the efficiency of the whole system and hence will lower prices. Kahlen et al. (2018) show results, where electricity prices decrease up to 3.4% on the wholesale market. We anticipate similar results in our research.

Third, VPPs can lead to a decrease in CO_2 emissions. With an increasing share of renewable energy production, the supply of sustainable electricity can excess total electricity demand at times of good weather conditions. The VPPs can consume this electricity by charging the EV fleet and the sustainable energy production does not need to be curtailed. The EV fleet can then feed the electricity back into the grid, when there is more demand than sustainable electricity production. Using this mechanism the total CO_2 emissions can be reduced.

3   Empirical Setting

We chose to embed our research in the German carsharing and electricity market. Germany has a comparably high share of renewables in its energy mix and is pushing for a energy turnaround[1] (German: *Energiewende*) since 2010. The high renewable energy content in the energy mix causes electricity prices to be more volatile, which makes Germany an attractive location for the use of VPPs. We obtained real-world trip data from Daimlers carsharing service Car2Go[2] and electricity market data from the European power exchange EPEX SPOT[3]. Additionally, we collected data from the German electricity market operator regelleistung.net[4].

3.1   Carsharing Fleets of Electric Vehicles

We think that the future of mobility will be electric, shared, smart and eventually autonomous. Carsharing companies are already contributing to the first two points by operating large fleets of electric vehicles. This research addresses the third point: Using EV fleets to smartly participate on electricity markets, without compromising

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[1] *Energy concept for an environmentally sound, reliable and affordable energy*, German Federal Ministry of Economics and Technology (BMWi), 2010.

[2] https://www.car2go.com

[3] https://www.epexspot

[4] https://www.regelleistungen.net

customer mobility. Carsharing providers like Daimler and BMW operate their car-sharing fleets in a free-float model, where customers can pick up and drop vehicles at any place withing the operating zone of the provider. Customers pay by the minute and are offered incentives to park EVs at charging stations. Analyzing free float trip data is substantially more difficult than fixed trip data. Individual trips have to be reconstructed using the GPS data of the cars and predicting the rental demand is a complex matter. Demand patterns differ depending at which place and at what time the EVs are parked. 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 Type
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 Charge
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

3.2 Electricity Markets

On electricity markets actors participate in auctions to match supply of electricity generation and demand of electricity consumption. Participants place asks (sale offers) and bids (purchase orders). The price is determined by an auction mechanism, which can take different forms, depending on the type of market. Germany, as many other countries, has an liberalized energy system in which the generation and distribution of electricity is decoupled. Multiple electricity markets exists, which

differ in their reaction time between the order contract and the delivery of electricity. Day-ahead and spot markets have a reaction time between a day and several hours, whereas in operating reserve markets the reaction time ranges from minutes to seconds.

The auction mechanism design is essential for electric markets (Kambil & van Heck, 1998). Electricity markets work according to the merit order principle. Resources are considered in an ascending order of the energy price until the capacity demand is met. The clearing price is determined by the energy price, at the point where supply meets demand. Payment models differ in the markets: In contrast to day-ahead market, where a uniform pricing schema is applied, in secondary reserve markets and intraday markets bidders get compensated by the price they bid for (pay-as-bid principle).

Carsharing Fleets can offer the capacity of their EV batteries on multiple markets at the same time to make use of the different market properties. On operating reserve markets prices are usually more volatile and consequently more attractive for VPPs. They also bear a higher risk for the fleet; commitments have to be made one week in advance, when customer demands are still of uncertain. To not face penalties for unfulfilled commitments only a conservative amount of capacity can be offered to the market. Spot markets allow participants to continuously trade electricity products up to fifteen minutes prior to delivery. At this point it is possible to predict if a EV is likely going to be rented out with a high accuracy. This creates the possibility to trade the remaining available capacity with a low risk at the spot market.

3.2.1   Secondary Operating Reserve Market

In this research we will use bidding data from the German secondary reserve market between 01.06.2016 and 01.01.2018. The data contain weekly lists of anonymized bids, where the electricity product, the offered capacity, the capacity price and the energy price of the placed bids are listed. As also negative prices are allowed, the payment direction is included as well. Moreover we find information about the amount of electricity accepted, i.e. either partially or fully. Bids which weren't accepted are not listed. An excerpt of the data can be found in Table 2.

Table 2: List of Bids of the German Secondary Reserve Market

Product[5]	Capacity Price[6]	Energy Price[7]	Payment	Offered[8]	Accepted[8]
NEG-HT	0	1.1	TSO to bidder	5	5
NEG-HT	0	251	TSO to bidder	15	15
NEG-HT	0	564	TSO to bidder	22	22
. . .	. . .	. . .	. . .	. . .	. . .
NEG-NT	0	21.9	Bidder to TSO	5	5
NEG-NT	0	22.4	Bidder to TSO	5	5
. . .	. . .	. . .	. . .	. . .	. . .
POS-NT	696.6	1200	TSO to bidder	5	5
POS-NT	717.12	1210	TSO to bidder	10	7

3.2.2 Intraday Continuous Spot Market

We will embed this research in the EPEX Spot Intraday Continuous market. The data have been provided by ProCom GmbH[13] and encompass order books and executed trades from 01.06.2016 till 01.01.2018. As displayed in Table 3, trades can have a very short lead time before delivery. Electricity products are: 30-minute contracts, hourly contracts and block contracts. The products can be traded up until 30 minutes before delivery (5 minutes in the same control area). Participants can submit limit orders at any time during the trading window and equally change or withdraw the order at any time before the order is accepted. Limit orders are specified as quantity/price pairs. When an order to buy (bid) and an order to sell (ask) is matched the trade will get executed. The order book is visible to all participants, hence it is known which unmatched orders exist at the time of interest.

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[5]NEG-NT = Product code for negative secondary control reserve to be provided between the hours of 00:00h and 08:00h as well as between 20:00h and 24:00h from Monday through Friday as well as all day on Saturday, Sunday and public holidays applicable to all of Germany. POS-HT = Product code for positive secondary control reserve to be provided between the hours of 08:00h and 20:00h from Monday through Friday.

[6]Capacity prices are in given in €/MW.

[7]Energy prices are in given in €/MWh.

[8]Capacities are given in MW.

[13]https://procom-energy.de/

Table 3: List of Trades of the EPEX Spot Intraday Continous Market

Execution time	ID	Unit price[14]	Quantity[15]	Buyer area	Seller area	Delivery date	Product[16]	Product time
2017-12-04 06:54:55	8031392	5100	5500	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:53:26	8031391	5900	10000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:53:26	8031390	5890	10000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:53:15	8031389	5230	7000	50Hertz	50Hertz	2017-12-04	H	08-09
2017-12-04 06:53:13	8031386	5900	500	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:53:13	8031387	5100	3600	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:53:13	8031388	5200	1400	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:53:02	8031385	5890	11000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:52:38	8031380	6000	10000	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:52:38	8031381	5750	8000	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:52:38	8031382	5800	2000	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:52:38	8031383	5890	4000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:52:38	8031384	6000	4000	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:52:27	8031379	5230	8000	50Hertz	50Hertz	2017-12-04	H	08-09
2017-12-04 06:51:33	8031378	6600	5000	TransnetBW	TransnetBW	2017-12-04	H	08-09
2017-12-04 06:51:28	8031377	5400	8000	Amprion	Amprion	2017-12-04	H	08-09
2017-12-04 06:51:24	8031376	5400	7000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:49:34	8031375	5100	4000	TenneT	TenneT	2017-12-04	H	08-09
2017-12-04 06:49:26	8031374	5400	5000	50Hertz	50Hertz	2017-12-04	H	08-09
2017-12-04 06:49:23	8031373	5510	8000	50Hertz	50Hertz	2017-12-04	H	08-09

4   Literature Review

1. Agent based sustainable society

2. Electric Vehicles, Smart Charging and Virtual Power Plants

3. Electricity Price Forecasting

- IS can help with climate change

- Use IS to align organizational goals with sustainability (carsharing and CO_2 emission) with DSS (Doing good by doing well)

- Use EV Fleets to align mobility goals with battery storage goals

- Demonstrate this with intelligent agent in an simulation similar to PowerTAC

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4.1   Smart Charging and Vehicle-to-Grid

Charging whole EV fleets at the same time can overload transformers and sub-stations, which causes severe problems to the grid (Kim, Tabors, Stoddard, & All-mendinger, 2012; Sioshansi, 2012). A proposed solution is smart charging: To reduce peak demand EVs get charged when the grid is less congested. Valogianni, Ketter, Collins, and Zhdanov (2014) find that using intelligent agents to facilitate smart charging, can be substantially beneficial for households. Kara et al. (2015) present results, where 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), where enabled EVs can discharge their batteries back into to 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), but they point out that battery technology and battery costs are a crucial factor. Tomić and Kempton (2007) show that V2G can profitable, especially when there is a high variability in electricity prices on the market. They find that a shorter interval between sale and physical delivery increases the benefits.

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[10]Unit prices are given in €c/MWh.

[11]Quantities are given in kW.

[12]Products: are: H = Hourly, Q = Quarterly and B = Block.

Successful trading strategies to participate on multiple markets have been found by Mashhour and Moghaddas-Tafreshi (2011b) using stationary storage. The authors use VPPs to participate on the spinning reserve market and day-ahead market at the same time. Similar research has been done by He et al. (2016). They take battery life cycle into account, which proves to be a decisive factor. In this thesis, we aim to jointly participate on the operating reserve and spot market with non-stationary storage, while considering 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 spot markets.

4.2 Electricity Brokers

- Studies have assumption that car owners or household can trade on wholesale markets, not realistic due to minimum capacity requirements

- Electricity Brokers (Ketter, Collins, & Reddy, 2013) introduced to act on behalf of a group

- (Brandt, Wagner, & Neumann, 2017) and (Kahlen, Ketter, & van Dalen, 2014)

4.3 VPP

- (Mak, Rong, & Shen, 2013)

4.4 Carsharing

- (Firnkorn & Müller, 2015) Freefloat carsharing reduce carbon emissions

- Wagner, Brandt, and Neumann, 2016

- Previous studies were trips known in advance: deterministic, free-float add uncertainty, per-minute

- EV either committed to be charged or discharged or free for renting. In reality trips are more spontaneous

- Offering EV capacity for control reserves not shown in business setting

- Other than (Kahlen et al., 2017; Kahlen et al., 2018) this has not been done yet.

- Kahlen present very conversative results and propose the combination of multiple markets in future work. In their approach the VPPs are mainly used to buy from the markets when electricity is cheap and thus charge their EVs basically for free (Citation). V2G is almost never used.

- We will build on Kahlen results and introduce an integrated bidding strategy. We will draw on previous results from

He et al., 2016; Mashhour and Moghaddas-Tafreshi, 2011b and act on multiple markets.

4.5   Electricity Price Forecasting and Neural Networks

In review papers of electricity price forecasting techniques Neural Networks (NN) play an essential role. Aggarwal, Saini, and Kumar (2009) found that 17 papers, which have published in relevant journals at the time, use NN models (including recurrent NN, and fuzzy NN) to forecast electricity prices. In comparison only 12 papers covered time-series and causal models. In a more recent review paper, Weron (2014) consider disjoint sets of papers, where 95 papers belonging in the 'neural network' category and 100 in the 'statistical time series' category. This shows the relevance of advanced AI and deep learning methods for electricity markets. To the best of our knowledge, these methods have not been considered for bidding on multiple electricity markets with EV fleets yet, as we aim to do. Another promising approach is the use of ensemble forecasting, where multiple forecasts are evaluated together to provide less risky predictions (Avci, Ketter, & van Heck, 2018).

4.6   Reinforcement Learning in Smart Grids

Previous research shows that intelligent agents equipped with Reinforcement Learning (RL) methods can successfully take action in the smart grid. Reddy and Veloso (2011a, 2011b) show that autonomous broker agents (Ketter et al., 2013), which aggregate distributed electricity producers and operate on different electricity markets, can learn their strategies using RL. Peters et al. (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 because future smart markets might change in their structure and intelligent agents should adapt to a variety of market structures and conditions. Valogianni et al. (2014) adopt RL methods

to learn electricity consumption behavior of households. The authors implement the 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.

RL is a perfect solution to learn the Problem for VPP composition, no time series where we can learn from.

- Reward Function: Overall profitability of the Fleet

- States: Predicted rental demand (i.e. battery capacity), Electricity prices on both markets

- Actions: Allocate capacity to VPP types.

Evaluated against a benchmark model, where the composition of VPP is just an optimization function of

5   Research Design

The research will be structured using the IS design science principles proposed Hevner et al. al. (2004). In Figure 1 the proposed research design is depicted. We will place a special focus on the used methodologies, the developed artifact and the evaluation of the results. Drawing from the *Knowledge Base*, multiple methods will be compared and evaluated against each other and thus emphasizing *Research Rigor*. Considering *Business Needs*, we will develop an *Artifact* in form of a decision support system. Evaluating the results with real-world data with a simulation will make sure the *Artifact* is *applicable in the appropriate environment* (i.e. carsharing fleets).

5.1   Problem relevance: Environmental (People), carsharing (Business)

5.2   Methodologies

Draw upon well researched statistical and machine learning methods: statistical pattern recognition, time-series forecasting and artificial neural networks.
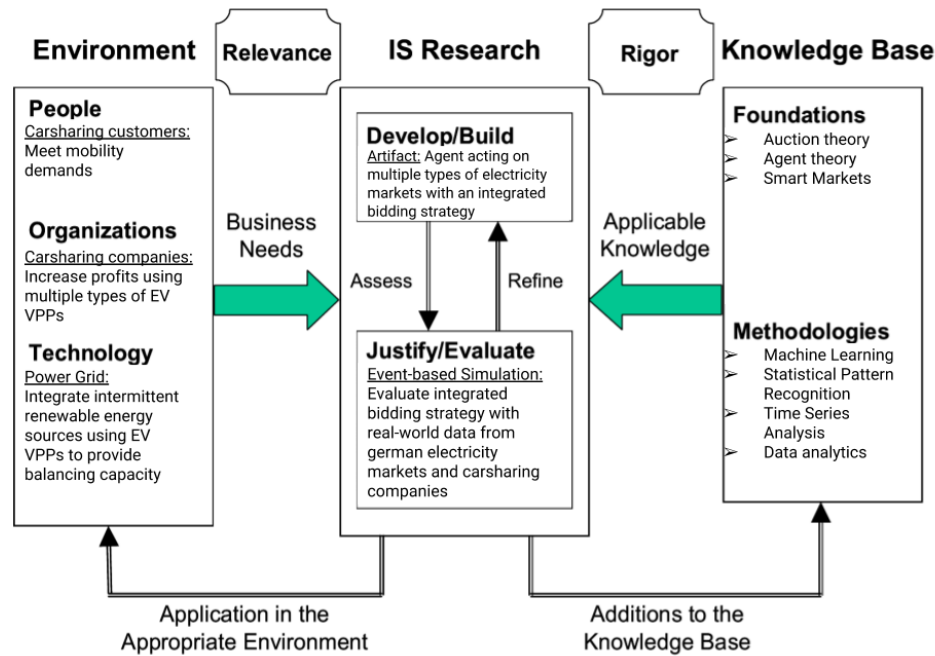
Figure 1: Research Design following Hevner et al., 2004

5.2.1 Quantitative Study

- What is the purpose of the study?

  1. EV Capacity Prediction / Demand Prediction
  2. Dynamic VPP Allocation Learning
  3. Determine Bids/Asks/Market: Price Prediction

5.2.2 ML-based Intelligent Agents

5.3 Artifact: Instantiation of an intelligent agent.

- Thus: An intelligent Agent is needed, which dynamically allocates parked, plugged-in EVs to be used as VPP or stay idle, depending whether an EV is likely going to be rented out and how much capacity it has available.

5.4 Evaluation: Event-based simulation using real-world data

-Using real-world data from German electricity markets and trip data from a carsharing provider.

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References

Aggarwal, S. K., Saini, L. M., & Kumar, A. (2009). Electricity price forecasting in deregulated markets: A review and evaluation. *International Journal of Electrical Power & Energy Systems*, 13–22. doi:10.1016/j.ijepes.2008.09.003

Avci, E., Ketter, W., & van Heck, E. (2018). Managing electricity price modeling risk via ensemble forecasting: The case of turkey. *Energy Policy*, 390–403. doi:10.1016/j.enpol.2018.08.053

Bichler, M., Gupta, A., & Ketter, W. (2010). Designing smart markets. *Information Systems Research*, 688–699. doi:10.1287/isre.1100.0316

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

German Federal Ministry of Economics and Technology (BMWi). (2010). *Energy concept for an environmentally sound, reliable and affordable energy.*

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

Hevner, March, Park, & Ram. (2004). Design science in information systems research. *MIS Quarterly*, 75. doi:10.2307/25148625

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.*

Kambil, A., & van Heck, E. (1998). Reengineering the dutch flower auctions: A framework for analyzing exchange organizations. *Information Systems Research*, 1–19. doi:10.1287/isre.9.1.1

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

Mak, H.-Y., Rong, Y., & Shen, Z.-J. M. (2013). Infrastructure planning for electric vehicles with battery swapping. *Management Science*, 1557–1575. doi:10.1287/mnsc.1120.1672

Mashhour, E., & Moghaddas-Tafreshi, S. M. (2011a). Bidding strategy of virtual power plant for participating in energy and spinning reserve markets-part i: Problem formulation. *IEEE Transactions on Power Systems*, 949–956. doi:10.1109/tpwrs.2010.2070884

Mashhour, E., & Moghaddas-Tafreshi, S. M. (2011b). 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*.

Reichert, S. (2010). Considerations for highly efficient bidirectional battery chargers for e-mobility. *E-Mobility. Technologien, Infrastruktur, Maerkte.*

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

Wagner, S., Brandt, T., & Neumann, D. (2016). In free float: Developing business analytics support for carsharing providers. *Omega*, 4–14. doi:10.1016/j.omega.2015.02.011

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International Journal of Forecasting*, 1030–1081. doi:10.1016/j.ijforecast.2014.08.008