The batteries of electric vehicles can be used as Virtual Power Plants to balance out frequency deviations in the electricity grid. Carsharing fleet owners have the options to charge an electric vehicle's battery, discharge an electric vehicle's battery, or keep an electric vehicle idle for potential rentals. Charging and discharging can be used to provide reliable operating reserves.

We develop an analytical model that manages carsharing fleets. On the one hand, the energy in the batteries of an electric vehicle can be made available to the grid as operating reserves. On the other hand, the electric vehicle can be made available for rental, where the location within the city matters: drivers want a car to be close to their place of departure or arrival. The model can also be used by Transportation Network Companies such as Uber to preposition their vehicles conveniently in a city or optimize zonal pricing.

To validate our model we develop a Discrete Event Simulation platform. We calibrate this simulation with locational information (GPS), rental, and charging transactions of 1,500 electric vehicles from the carsharing services Car2Go (Daimler) and DriveNow (BMW) over several years. We investigate the influence of the charging infrastructure density, battery technology, and rental demand for vehicles on the payoff for the carsharing operator and make an international comparison between the USA, Germany, the Netherlands, and Denmark. We show that Virtual Power Plants of electric vehicles create sustainable revenue streams for electric vehicle carsharing companies without compromising their rental business.

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MICHA T. KAHLEN - Virtual Power Plants of Electric Vehicles in Sustainable Smart Electricity Markets

ERIM

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Virtual Power Plants of Electric Vehicles in Sustainable Smart Electricity Markets

Virtuele energiecentrales van elektrische voertuigen in duurzame en slimme elektriciteitsmarkten

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus

Prof.dr. H.A.P. Pols

and in accordance with the decision of the Doctorate Board

The public defense shall be held on

Friday the 15th of September 2017 at 13:30 hrs

by

Micha Tobias Kahlen
born in Moosburg an der Isar, Germany.

Erasmus University Rotterdam

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Foreword

First, and foremost I would like to thank you, Wolf, for your continuous support, believing in me and my work, and giving me the space to develop my own work while at the same time stimulating me to excel. Your energy and enthusiasm inspired me and I highly appreciate your way of working where, next to hard work, there is also room for energy center outings to Alcatraz, Trier, or dinners at home in de Tuin.

Alok, your feedback helped me to position my work appropriately and taught me how to write crisp papers. In particular, I am very grateful that you have backed me in my papers also with negative reviews. I know that you are busy and therefore appreciate it even more that you made the time to meet with me and Wolf so often, despite various time zones.

Thank you for being such an amazing host in Berkeley, Tom. Your feedback, sitting down together with me to improve both writing and statistical models is unmatched. Your critical thinking and your way of challenging ideas and assumptions make it fun to work with you.

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Prof. Bettzüge thank you for going beyond your role as a reviewer. Your expertise on energy markets helped me to positioning the findings in the right context, and your constructive and very thorough feedback enabled me to bring the quality of my dissertation to the next level.

I would also like to thank the members of my thesis committee Thomas Y. Lee, John Collins, Alok Gupta, Marc Oliver Bettzüge, Eric van Heck, Jan van Dalen, and René de Koster for making it all the way from California, Wisconsin, Minnesota, Cologne, and Rotterdam to my defense. Thank you for your constructive feedback, support, and challenging questions.

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Ingrid, Cheryl, and Carmen thank you for all your administrative support. You are the glue that holds our department together.

Credits for one of the most visible parts of my thesis, the cover image, go to Vanessa. Thank you for going through so many iterations to design the image despite the workload of your own Bachelor thesis - it turned out to be perfect.

Without my colleagues I could not have done the PhD. Konstantina, your guidance and feedback, which started already during my master thesis, helped me tremendously to get started in my PhD. Derck, our trips adjacent to conferences from getting lost in the snow to road trips in the desert made the PhD an adventure. Christina, thank you that I could always rely on you for a good chat and sharing the pains and gains as German PhDs in the Netherlands. I would also like to thank Markus, Ksenia, and Yashar for our great work and time together.

Ein riesiges Dankeschön geht an meine Familie. Ohne euch wäre ich nicht der Mensch der ich heute bin. Meinen Eltern Regina und Rainer dafür, dass ihr mir immer zugehört habt, euren Rat und natürlich das Korrekturlesen. Jannis für deine kritischen Rezensionen meiner Arbeit aus der Perspektive eines Dr. Insch. der Elektrotechnik und den unvergesslichen research visit in Berkeley. El toda voor je hulp met Nederlandse vertalingen, je steun, liefde, en de leuke tijd die we er samen van gemaakt hebben. Auch vielen lieben Dank an den Rest der Familie für eure Unterstützung: Oma Tinni, Opa Willi, Oma Minchen, Opa Klaus, Moni, Norbert, Leon, Renate, Juppi, Colli, Dirk, Mats, Gerda und Bernd.

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Rotterdam, July 2017
Micha Kahlen

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Chapter 1

Introduction

With a growing world population, urbanization, and depleting resources we need to pursue a sustainable society. Two critical aspects for a sustainable society are electricity generation and transportation. With a transition to a more sustainable electricity production with wind and solar power, for example, the electrical grid becomes decentralized and more weather dependent. These changes need to be addressed appropriately to maintain a stable grid. Additionally, there are two disruptions in the transportation industry. On the one hand, electric vehicles (EV) start to gain traction in urban areas. This electrification of transportation creates new challenges for the electrical grid, as it was not designed to accommodate large numbers of EVs. On the other hand, there is a trend to fleet management of vehicles. Transportation Network Companies like Uber and Lyft but also carsharing companies like Car2Go, DriveNow, and Zipcar become increasingly popular. In this dissertation, we analyze the synergies that can be achieved by combining these trends with information technology and electronic markets.

Electricity markets are auctions where participants can buy and sell electricity to match demand for electricity and supply of electricity generation. To match participants *asks* (sell orders) and *bids* (buy orders) optimally we rely on smart electronic market structures. Smart markets are auction mechanisms that rely on optimization techniques to match demand and supply (McCabe et al., 1991; Gallien and Wein, 2005; Bichler et al., 2010; Ketter, 2014). We consider these markets from a participant's perspective to optimally allocate the fleet owners' vehicles.

EV fleet owners can leverage information technology to their advantage. By tracking vehicle locations remotely in real-time they can learn customer behaviors and driving habits to optimally allocate their vehicles. We develop decision support systems that structure this information to anticipate rental transactions and increase the utilization of the fleet. One way to increase the fleet's utilization is by selling the storage of EV batteries to electricity markets as virtual power plants (VPP) at times when no rental transactions are expected. VPPs are in this case an aggregate of several individual vehicles that act as a collective entity on the electricity market to conform to the market's minimum trading volume requirement (Pudjianto et al., 2007). Due to an increase in weather dependent renewable energy sources, the storage, from for example EVs, becomes increasingly important in electricity markets. For example, storage can bridge time windows of lower wind energy production volumes or reduce frequency deviations from cloud cover on solar farms.

An optimal allocation of a fleet of EVs has to make a trade-off between the payoff of potential rental and storage transactions. However, the payoff for rental transactions is much higher than for selling the storage on electricity markets, which we explicitly incorporate in our work as asymmetric payoffs. Therefore, fleet owners would allocate vehicles for rental transactions rather than selling their storage when they are in doubt whether a customer might rent the vehicle at a given time. Next to determining the bid quantity of energy that should be bought to charge the vehicles and the ask quantity sold to discharge them, a crucial component is the price at which this is to be done. Fleet owners are interested to sell electricity from its storage at times when prices are high and buy electricity at times when prices are low. In this work we show how vehicles should be allocated over time between being available for rental, charging, and discharging and the corresponding prices. The corresponding prices are based on the opportunity cost from renting, the cost of charging the vehicle with retail tariffs as benchmark, and the the cost of battery wear and tear. In this dissertation, we forecast the demand for vehicles first. Secondly, we use the demand information to sell the remaining storage in energy markets.

1.0.1 Carsharing Fleet Operation

We analyze the potential of EV carsharing fleets to participate in electricity markets without compromising the rental business of carsharing providers. We consider the vehicles of the carsharing providers Car2Go (Daimler)[1] and DriveNow (BMW)[2]. We track and analyze the GPS information and rental transactions of more than 2,700 vehicles in Amsterdam, Berlin, Copenhagen, San Diego, and Stuttgart in the

[1] `www.car2go.com`
[2] `www.drivenow.com`

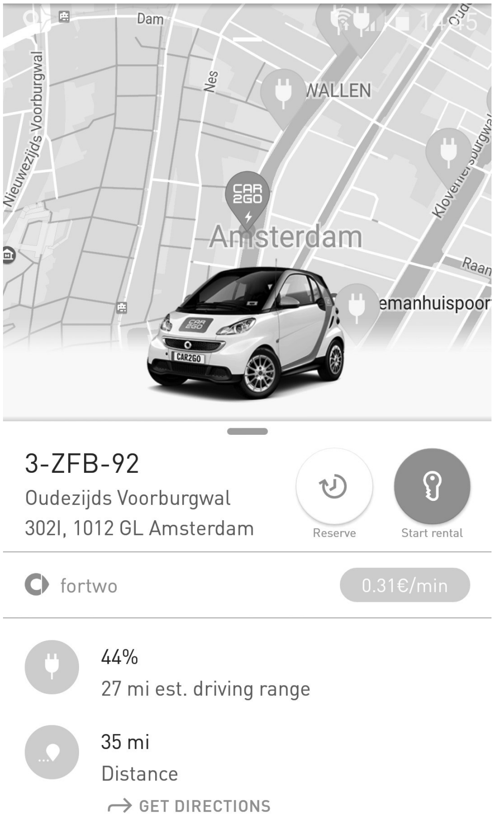

Figure 1.1: An example of a carsharing app (Car2Go) showing the location, state of charge, and rental price of a vehicle.

period from 2014-2016. We reconstruct vehicle paths from discrete GPS information. Analyzing the data is particularly complex for Car2Go and DriveNow, as they are free float carsharing companies. Free float means that the vehicles are not bound to specific stations, but can be freely picked up and dropped off at any public parking spot within the operating area in a city. Reservations can be made up to 30 minutes in advance via an app. For an example of the Car2Go reservation app, see Figure 1.1, showing the location, range, and price of a particular vehicle. The vehicles can be rented by the minute and customers get free minutes, if they return vehicles with a low battery (<20%) to any charging station.

Free floating fleets that are not bound to specific stations are complex to analyze as they can be located virtually anywhere in the city and the demand for vehicles needs

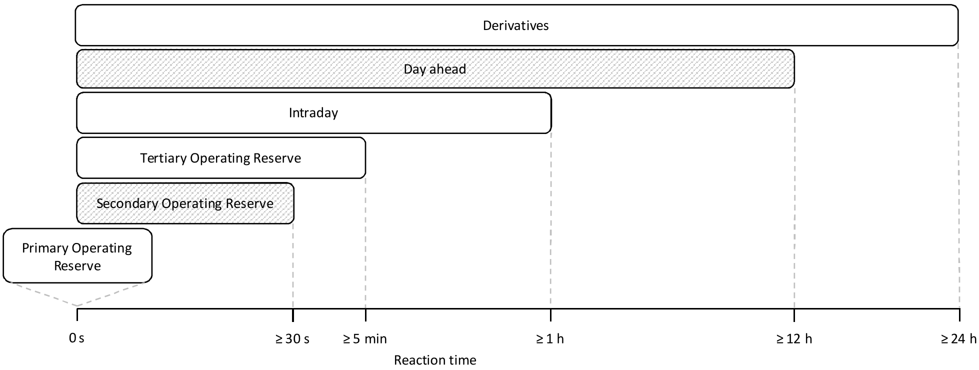

Figure 1.2: The typical electricity markets in a liberalized energy system. We focus on the secondary operating reserve markets for frequency regulation and the day-ahead market for the scheduling of EV charging sessions.

to be determined for all of these points. To predict demand we use hexagonal tiles in our models to partition the city into areas and use historical demand data, points of interest, and weather data as predictive variables. Hexagonal tiles are advantageous because the distance from one cell to all adjacent cells is the same. Besides for VPPs of EVs, our model can also be used for the optimal prepositioning of vehicles (Roy et al., 2014).

1.0.2 Electricity Markets

In liberalized energy systems, where the production and distribution of electricity is separated, there are several energy markets. Fleets of EVs could sell their storage on all of these energy markets to benefit from price differences over time. However, not all of them are equally well suited for this purpose. In principle the markets are different from each other in terms of their reaction time between the contractual agreement and physical delivery of electricity. This ranges from more than 24 hours, or usually several months or years in advance in derivative markets, over day-ahead and spot markets where the reaction time is usually several hours, to operating reserve markets, where the reaction time is restricted to several minutes or seconds only. Figure 1.2 shows the energy markets that typically exist in liberalized energy systems and their reaction times.

We would like to determine whether EVs can be used for arbitrage in electricity markets. For example low electricity demand at night causes lower electricity prices than during peak hours. This is interesting for long charging sessions that could benefit from paying lower electricity prices. The suitable market setting for this is the day-ahead market, which covers the hourly differences in a day.

Another issue we explore is whether EVs are suitable to balance out frequency deviations in the grid, to serve as backup power if another power source does not deliver the electricity as contractually agreed. For this purpose, vehicle-to-grid (V2G), where vehicles sell electricity back to the grid, could support the grid. The suitable market setting for this are operating reserve markets, with a short reaction time. We focus on the secondary operating reserve market as it is the market with the shortest reaction time, which reduces competition from power plants that cannot ramp their production up or down quickly enough to participate in this market. We do not focus on primary operating reserves because fulfilling the requirements to participate would make the charging poles too expensive.

We have chosen both a balancing market and a day-ahead market as they are the opposite ends of the physical delivery markets in terms of the reaction time (derivatives are financial instruments that are physically delivered in markets with lower reaction time). While the day-ahead market serves as a strategic balancing with differences across hourly time blocks during the next day, the balancing market reacts to the grid frequency as is. These are two very distinct needs by the grid, which is why we consider them in isolation.

Within this dissertation we also evaluate how decentralization and increasing levels of renewable energy sources change the market structures and prices and thereby have an influence on VPPs of EVs. However, EVs are only one solution to address the challenges that come along with the decentralization. And they will not be able to take on these challenges alone. Other important areas are, for example, more cross border cooperation between countries (Bettzüge, 2015).

Auction market design and its mechanisms are important for a proper market functioning (Kambil and Van Heck, 1998). Therefore we will briefly explain the market mechanisms of both selected markets in more detail. Both markets operate according to the merit order and prioritize cheaper resources, but the compensation of market participants is different:

The day-ahead market mechanism works according to the double auction principle, where all accepted *bids* (buyers) and *asks* (sellers) pay or are paid the same market clearing price regardless of their submitted price (Krishna, 2002).

The secondary operating reserve market mechanism works according to the 'pay-as-bid' auction principle, where all accepted bids pay and asks are paid their submitted price. In contrast to the day-ahead market the secondary operating reserve market is a two tiered auction that differentiates between the capacity price, a fixed price that is paid for the availability of a resource, and an energy price, a variable price that pays for the energy that is generated (International Grid Control Cooperation, 2014). Note that the auction mechanism differs slightly between the US and Europe, but the principles remain the same.

The differences in market mechanisms and the resulting compensation also leads to different pricing strategies for market participants. While the double auction already includes a profit margin by default, which is the difference between the submitted price and the market clearing price, the price submitted to a pay-as-bid auction needs to include an additional margin to make a profit. On top of that the pay-as-bid auction also needs to specify a fixed price for the capacity to participate in the market.

Buying and selling energy on the day-ahead market or the secondary operating reserve market is not mutually exclusive. In fact, fleets could even participate in other markets such as other operating reserve- or intraday markets. The advantage of participating in more than one market is that one can take advantage of the highest and lowest prices of all markets rather than on only one market, which increases the margin for the fleet owner. However, we study each market in isolation to make an assessment of each market respectively, which is a conservative estimate of the potential benefits from all three markets.

1.1 Main Contributions

First, we create a model that predicts the demand for vehicles within a city. This model relies on several indicators, such as weather, points of interest, and historical data to predict mobility demand across time and space. We show its usefulness with a prepositioning algorithm that relocates vehicles within a city based on the expected demand to maximize profits for fleets.

Second, we develop a pricing strategy for VPPs of EVs to sell the storage on the pay-as-bid secondary operating reserve markets. In this case we predict the inverse of the demand for vehicles; with machine learning algorithms we find times and spaces where there are vehicles but no demand for them. Machine learning based prediction models are most appropriate in this setting as they have high prediction accuracy. We have also tried other methods such as time-series and linear regression models, which were significantly outperformed by the machine learning methods. The demand information can be used to sell the storage of EVs located there. We use a stochastic process, where at no point in time or space it is impossible that a vehicle is rented. However, the expected profits are at some times closer to zero than at other times. This is incorporated in the pricing scheme to sell or buy electricity in the market, which changes over the course of a day. We also make an international comparison between the USA, Germany, and the Netherlands and how international market differences influence VPPs. We find large differences in the charging infrastructure density in the different countries that play an important role for the availability of EVs and their potential to sell storage. To investigate this further we conduct a sensitivity analysis. In this analysis we show how the profits would change if one would place charging stations at the most frequently visited parking spots.

Third, we develop a pricing strategy for VPPs of EVs to sell storage on the day-ahead market. Also in this case we predict the inverse of the demand for vehicles; but we use the sinusoidal, daily and weekly repeating patterns of demand per area to predict the quantity of storage available. We primarily participate in the market to charge the fleets at a discount when energy is cheap. Therefore we place bids and asks on the electricity market's demand and supply curve. As we have the individual bids and asks of the market, we can increase the number of bids and asks to charge and discharge EVs. As we increase the number of fleets in the market, we observe changes in the market equilibrium that have an energy system wide positive effect. A double auction is particularly suited to demonstrate this effect on the merit order, as all market participants are paid the same price and benefit in an equal manner from the changes in the market.

Table 1.1 highlights the different dimensions of contributions across the chapters of this dissertation. The rows of the table reflect whether the chapter is concerned with the demand for mobility and the corresponding quantities of vehicles and storage or whether it is concerned with the pricing of the storage from these vehicles. Note that the classifications in this table are tendencies only. While Chapter 2 is primarily concerned with the quantities and Chapter 3 and 4 are primarily concerned with the pricing, the quantities and prices are intertwined, i.e. at higher prices one can commit a larger quantity of EVs and vice versa. However, the application areas are different as well. While Chapter 2 is concerned with mobility only, Chapter 2 and 3 are on the intersection of electric mobility and energy markets. The columns of the table differentiate between these energy markets in terms of the reaction time. The reaction is the time between the contractual agreement and the physical delivery of electricity. The demand forecasts from Chapter 2 can serve as input for both short (approximately 30 seconds) and medium (between 12-36 hours) reaction times. The

Table 1.1: Overviews of this dissertation's contributions on the dimensions order (quantities and pricing) and reaction time (short and medium).

	Reaction time to physical delivery	
Order	**Short (seconds)**	**Medium (hours)**
Quantity	Demand forecasting (Chapter 2)	
Price	VPP pay-as-bid auction (Chapter 3)	VPP double auction (Chapter 4)

main difference between Chapter 3 and 4 is the reaction time. Chapter 3 discusses the suitability of EVs to function as VPPs in operating reserve markets to stabilize the grid in the very short term and balance out frequency deviations in the seconds range. This is tested in the secondary operating reserve market with a pay-as-bid auction that includes both a price for capacity (fixed) and energy (variable). Chapter 4 discusses the suitability of EVs to function as VPPs in the day-ahead market to benefit from price differences over the course of the day to charge vehicles at a discount. This is primarily a demand management measure to move excess demand from EVs to times when the grid is less congested. While the problem set-up from a methodological perspective of Chapter 3 and 4 is similar, which makes them better comparable, they are different beyond the reaction time. In particular, Chapter 3 is predominantly delving into the bidding strategy and considering the individual elements to arrive at an optimal pricing strategy. This is critical for fleet owners who have to deploy the vehicles. Chapter 4, whilst also considering the bidding strategy, is additionally concerned with the scalability for larger fleets at a macro level and its economic implications, including competition. This is critical for the societal implications. For an overview of the main differences between Chapter 3 and 4, see Table 1.2.

1.2 Practical Relevance

The results of this dissertation are directly relevant to the operations of carsharing companies such as Car2go or DriveNow. We show how they can increase their profits by participating in energy markets with idle EVs, how they should price the storage, and what quantities they should offer as not to compromise their rental business. As

Table 1.2: Overview of the main differences between Chapter 3 and 4.

	Chapter 3	**Chapter 4**
Data	Energy prices of secondary operating reserves in USA, Germany, Netherlands	Energy prices of Day-ahead ELSPOT Noord Pool Spot in Denmark
Auction mechanism	Pay-as-bid	Double auction
Market type	Capacity and energy market	Energy market
Commitment timing	4-11 days in advance	12-36 hours in advance
Pricing strategy	Optimal prices that reflect the complex cost structures of fleets	Scalable heuristic
Storage availability	Machine learning based model	Time-series sinusoidal model
Endogeneity	Fleet is price taker, since it serves only a small proportion of the market	Scenario analysis of how the market equilibrium would behave if up to 100% of vehicles were electric
Programming language	R, since it is a small scale optimization model	Java, since it is a scalable model for multiple fleets

selling storage is not their core business but extends the profits, they may consider to collaborate with companies that have experience in bringing VPPs to the energy markets such as for example Next Kraftwerke[3] or other energy companies. There are companies such as Jedlix[4] or The Mobility House[5] that already actively pursue vehicle-2-grid technology. Jedlix uses the flexibility that customers provide them with in their EV charging process via an app to balance their energy portfolio. The Mobility House uses second life batteries of EVs to provide primary operating reserves, and pursue a similar strategy for its EV customers.

However, non-stationary batteries do not meet the current prequalification criterion for the secondary operating reserve market. Nevertheless, companies can still use our models to balance their portfolio. That way they do not get paid for their services but do not have to pay the imbalance penalties. This is for example done by Jedlix and has two effects. The first effect is that the demand for reserve power decreases because the imbalance settlement is shifted towards the producers. The second effect is that the batteries are used for portfolio management and are not committed to operating reserves anymore potentially causing a lack of competition.

A more recent development in Germany is that the Transmission System Operators (TSO) report that the increase in renewable energy sources caused a decrease in the demand for operating reserves and a more stable frequency, even though the opposite was expected. On the one hand, this decreases the need for storage from EVs, but on other hand, it also makes it more manageable by storage only when fossil fuel based power plants that currently dominate the balancing market will be phased out.

1.3 Outline

The dissertation is structured as follows. In Chapter 2 we will discuss how fleets can forecast mobility demand and use this to preposition vehicles accordingly. Then, in Chapter 3 we will use mobility demand forecasts to participate in frequency regulating operating reserve markets. Next, Chapter 4 will discuss how EVs can shift their charging behavior to off-peak hours and how this influences the market equilibrium. Then, we will conclude our work in Chapter 5 and will provide directions for future research.

In the following we present a brief abstract of each chapter of this dissertation.

[3] `www.next-kraftwerke.com`
[4] `jedlix.com`
[5] `mobilityhouse.com`

Chapter 2 - Abstract Companies providing mobility solutions, such as Uber, Lyft and a host of short-term car rental companies, can generate value from information technology to track their vehicles location. Real-time decision making to act on this information is critical for the success of one-way mobility companies. We show how these companies can predict vehicle demand with high accuracy for vehicles across time and urban areas. We validate this model by tracking the movement and transactions of 1,100 vehicles from the carsharing service Car2Go in Berlin. With our model they could preposition vehicles to increase service levels with a smaller fleet. The accuracy of the model to predict demand areas and times is a key contribution to urban mobility systems. Prepositioning vehicles based on expected demand and supply as modeled in our paper are vital to the business models of emerging transportation network companies like Uber and will be indispensable for autonomous vehicles.

Chapter 3 - Abstract Electric vehicles have the potential to be used as virtual power plants to provide reliable back-up power. This generates additional profits for carsharing rental firms, who rent vehicles by the minute. We show this by developing a discrete event simulation platform based on real-time locational information (GPS) of 1,100 electric cars from Daimlers carsharing service Car2Go in San Diego, Amsterdam, and Stuttgart. We design trading prices (bids and asks) for participating in the respective operating reserve markets, markets for back-up power guaranteeing replacement when a power source fails, to sell the storage from idle electric vehicles. These trading prices are calibrated and tested with operating reserve market data. We investigate the influence of the charging infrastructure density, battery technology, and rental demand for vehicles on the payoff for the carsharing operator. We show that virtual power plants create sustainable revenue streams for electric vehicle carsharing companies without compromising their rental business.

Chapter 4 - Abstract Virtual power plants (VPP) play a crucial role in balancing the electricity smart grid. VPPs aggregate energy from decentralized sources, for example, biogas, solar panels, or hydropower, to generate and consume electricity on demand. We study the management of electric vehicle (EV) fleets organized in VPPs as a way to address the challenges posed by the inflexible energy supply of renewable sources. In particular, we analyze the potential of parked EVs to absorb electricity from the grid, and provide electricity back to the grid when needed. A fleet owner can either charge (add inventory), discharge for renting (decrease inventory), discharge to the grid (decrease inventory), or keep an EV idle (no change in inventory). A unique property of our model is that inventory decisions are made between making an EV available for rental, where the location within the city matters (drivers want a car to be close to their place of departure or arrival) and for discharging it to the grid, where location does not matter (vehicles can discharge to the grid from any capable charging point). We study the feasibility of VPPs for a fleet of 1,500 real EVs on the 'Nord Pool Spot', a North European electricity spot market. A sinusoidal model captures the demand patterns of car-sharing vehicles accurately, especially when our mean weighted (MAS) objective function with asymmetric payoffs is applied. We show that the VPP can be profitable to fleet owners, ecologically advantageous through reductions in emissions, and beneficial for consumers by reducing energy expenses.

Chapter 5 In Chapter 5 we will revisit the most important conclusions and findings from Chapter 2-4, put them in perspective, and give an outlook on future work.

1.4 Declaration of Contribution

Chapter 1: This chapter is written by the author of this thesis.

Chapter 2: This chapter is joint work from the author of the thesis, Prof. Dr. W. Ketter, Dr. T.Y. Lee, and Prof. Dr. A. Gupta. The author of this dissertation is the first author of this chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper was done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 3: This chapter is joint work from the author of the thesis, Prof. Dr. W. Ketter, and Prof. Dr. A. Gupta. The author of this dissertation is the first author of this chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper was done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 4: This chapter is joint work from the author of the thesis, Prof. Dr. W. Ketter, and Dr. J. van Dalen. The author of this dissertation is the first author of this chapter and has done the majority of the work. The data collection, data analysis, programming, algorithm implementation, testing, and writing of the paper was done by the author of this thesis. The co-authors of this Chapter contributed by structuring the Chapter, improving modelling aspects of the paper, giving it more focus by rewriting parts of the Chapter, providing significant guidance, and feedback. Without the co-authors this Chapter would not have been possible in its current form and quality.

Chapter 5: This chapter is written by the author of this thesis.

Chapter 2

Optimal Repositioning and Fleet Sizing to Maximize Profits for One-Way Transportation Companies [1]

2.1 Introduction

Catching a ride after a big event, such as a concert or a football game, is virtually impossible, because of a sudden peak in demand. New one way transportation fleet initiatives, such as carsharing (Car2Go, DriveNow, Zipcar), transportation network companies (Uber, Lyft), and autonomous vehicles use real-time information about where vehicles and customers are in order to efficiently match them. But to deal with huge events that cause a sudden surge in demand or structural demand changes, such as rush hours fleets, needs proactive decision-making. These events need to be

[1] This paper is currently under peer review at the International Conference on Information Systems 2017.
Parts of this chapter appear in the following conference proceedings:
Kahlen, M.T., Ketter, W., Lee, T., Gupta, A. (2017). Optimal Prepositioning and Fleet Sizing to Maximize Profits for One-Way Transportation Companies. *38th International Conference on Information Systems (ICIS).* Seoul, South Korea (10-13 December 2017).
Kahlen, M.T., Visser, S., Ketter, W., Lee, T., Gupta, A. (2017). Geospatial Analytics: Predicting Cost-Effective Charging Infrastructure Locations and Service Levels. *2017 Winter Conference on Business Intelligence.* Snowbird, United States (2-4 March 2017).

anticipated and acted on in advance by repositioning vehicles accordingly to increase service levels and profits.

However, current operations of fleets simply match vehicles with the closest vehicle to the customer that is available. We find that fleets leave a lot to chance and thereby money on the table. We show that firms can decrease pick-up time by proactively repositioning vehicles within a city to meet expected demand. With the new technology to track vehicles and transactions, which is already used in these fleets, we build a model that can accurately forecast demand and reposition the fleet accordingly. Intelligent repositioning increases vehicle utilization, which in turn decreases fleet size requirements. We investigate the dual optimization of vehicle repositioning and fleet size to maximize profits for one way transportation companies. We define one way transportation companies as those that own a fleet of vehicles within a city and offer mobility services to customers. These fleets are not bound to specific pick-up and drop-off locations. This is also referred to as "free float."

The objectives of this chapter are the following:

[1] Construct a location dependent model to predict vehicle demand.

[2] Present a two-stage, greedy, hill-climbing algorithm for simultaneously optimizing fleet size and fleet allocation.

We develop a two-period model where vehicle demand in period one defines the expected supply of vehicles for period two. Vehicle demand in period two defines the expected demand for period two. The difference between expected demand and expected supply in period two characterizes the opportunity for gain by repositioning vehicles. The first objective helps us to develop an understanding of the expected demand and supply, while the second objective shows how and to what extent fleets can benefit from a location dependent demand model by using this information to reposition the vehicles in their fleet.

For the first objective, we develop a regression model to predict the rental transactions for a given time interval and geographical area. The model to predict demand includes independent variables, such as Google map points of interest (restaurants, museums, bus stops, and so on), the weather, the day of the week, the hour of the day, and historical vehicle usage in this area.

The vehicle demand prediction serves as input to a re-positioning algorithm for optimizing the fleet size and location. Conditioned on fleet size, we define a reassignment of vehicles to balance supply and demand. We find the optimal fleet size based on an objective function that includes both the fixed costs of owning the fleet and the variable costs of maintenance. We also include the costs of repositioning. We show that profits, which include these costs, are a concave function that has a global maximum. The cost functions to relocate vehicles differentiate between free float carsharing with high repositioning cost as they have to hire additional employees, transportation network companies with medium repositioning cost as they already have drivers in the vehicles, and autonomous vehicles with low cost for repositioning cars.

We evaluate the prediction model on data from Car2Go `www.car2go.com`. We test our model with a fleet of 1,100 free float carsharing vehicles in Berlin over the period from September - December 2016. During this time the vehicles were rented more than 300,000 times. Additionally, we have analyzed more than 200,000 points of interest from Google maps in Berlin as demand indicators. In a rolling time window, we fit the model with 60 days of data and predict the demand in the upcoming hour. We repeat this for the period from September - December 2016 and provide a sensitivity analysis of the training set size. The evaluation of the prediction model is based on the root mean square error (RMSE) and mean average deviation (MAD).

We evaluate the optimization of vehicle repositioning through simulation, based upon data from Car2Go. We show that profit increases of 3% for free float carsharing, 6% for transportation network companies, and 7%, for autonomous vehicles can be achieved with our demand prediction model and assignment algorithm. The differences are due to varying relocation costs, which are high for carsharing and low for autonomous vehicles.

Our primary contribution is a highly accurate demand prediction model for mobility demand in urban areas that differentiates the time of the day. We take the number of vehicles into account and the way they influence the observed demand. This is indispensable information for fleet owners, such as carsharing companies or transportation network companies. Based on this information they can reposition their vehicles or enhance zonal pricing models. We demonstrate the usefulness of this contribution in a simulation based upon historical priors from Car2Go in Berlin to reposition vehicles.

2.2 Related Work

Recent discussions in the information systems (IS) community have highlighted the importance of IS in solving societal challenges in cities (Brandt et al., 2016). These challenges, among which mobility is a crucial factor, can be solved with information technology. This has been shown by Ketter et al. (2016a) in the energy field. We show how IS can contribute to enhanced urban transportation systems that proactively react to demand to reduce the need for resources such as vehicles and reduce the cost of mobility.

Facility relocation is an established area of research to make location decisions for service stations that differ geographically (Wesolowsky and Truscott, 1975; Owen and Daskin, 1998; ReVelle and Eiselt, 2005). Even though it is not always simple, as there are many strategic issues for companies involved with multiple objectives in making the location decisions, the main decision parameters are service level and cost reductions. Halper et al. (2015) looked at relocations in the context of mobile facility locations. Similarly, ReVelle and Eiselt (2005) have looked at ambulance positioning within a city. The objectives and methods are well understood and can be applied to the carsharing industry where better vehicle location decisions improve the customer service. Wagner et al. (2016) created a regression model to predict demand for carsharing based on points of interests and demographic factors within a city, to expand operating areas. They have tested their expansion algorithm against real carsharing data to validate it. However, they do not include seasonality or an analysis of the marginal effects of time of day, day of week, and historical demand explicitly in the regression, which is important for the repositioning of vehicles in our setting.

All of these studies consider investment decisions over longer periods in time, while there may be significant demand differences over the day, and prediction methods such as economic regimes that take real-time demand forecasts into account to make decisions (Ketter et al., 2012) are needed. These have to take into account dynamic preference modeling and decision recommendations (Bichler et al., 2010). Preference modelling is important to predict demand and decision recommendations. There is a growing body of literature that has applied real-time forecasting and decision making to carsharing to optimize fleet usage.

Kek et al. (2009) and Bruglieri et al. (2014) have studied the problem of relocation of vehicles in carsharing systems with prespecified stations over the city to meet peak demand while reducing relocation cost. They work with thresholds; if the number of vehicles at a station drops below a certain threshold, vehicles are relocated to this station. They validate their model with a carsharing fleet in Singapore and find that reductions between 5-13% of zero-vehicle-time over all stations are possible (Kek et al., 2009).

Recent studies by Wagner et al. (2015) and Febbraro et al. (2012) tackle an even more complex relocation problem to relocate vehicles of free float carsharing services, where vehicles can be picked up and dropped off at any parking spot in the city and are not bound to specific stations. Demand in this location is much more complex to forecast, because it is not bound to specific locations and there is a lot of unobserved demand in areas where, for example, no vehicles are present at a specific point in time. These studies use and predict the utilization of vehicles in a specific area to relocate vehicles. The relocation is performed by customers by providing them an optional financial incentives if they leave or move vehicles to desired locations that are expected to have a higher utilization. Wagner et al. (2015) take a snapshot of demand and supply and generalize to situations with varying demand and supply. They use the expected utilization in an area to relocate vehicles to high utilization areas. While using expected utilization is easy to implement there are also drawbacks to it. The utilization of vehicles is not a precise indicator for relocations. For example, in an area where there is only one vehicle that was rented in a given time interval, the utilization was 100%. But this does not necessarily mean that a second car that is moved there would be rented out, too, as it depends on the demand. The same applies to an area where there is one vehicle and demand for one vehicle, which in terms of utilization is the same as an area where there are 10 vehicles but there is demand for 20 vehicles. We explicitly include and separate between expected demand and available vehicles to overcome this utilization issue. Furthermore, there is also an issue of observed demand, as fleets are not aware how much additional demand can be expected on top of the vehicles rented in an area, if there were more vehicles. We bypass this issue by serving the observed demand with a smaller fleet size. The main differences between Wagner et al. (2015) and our approach is that we use the difference between expected demand and supply rather than the percentage of utilization, and that we do a "dual optimization" of fleet size and relocation. So, the overall objective function is different and the optimization is more complex, which is a classic disequilibrium problem. Another difference is that we consider the relationship between variables such as weather, points of interest in the vicinity, the rating and price of points of interest in the vicinity. Wagner et al. (2015) only look at historical data. The advantage is a higher granularity in predicting the rental demand and that our model is transferable to other cities just by knowing where the points of interest are.

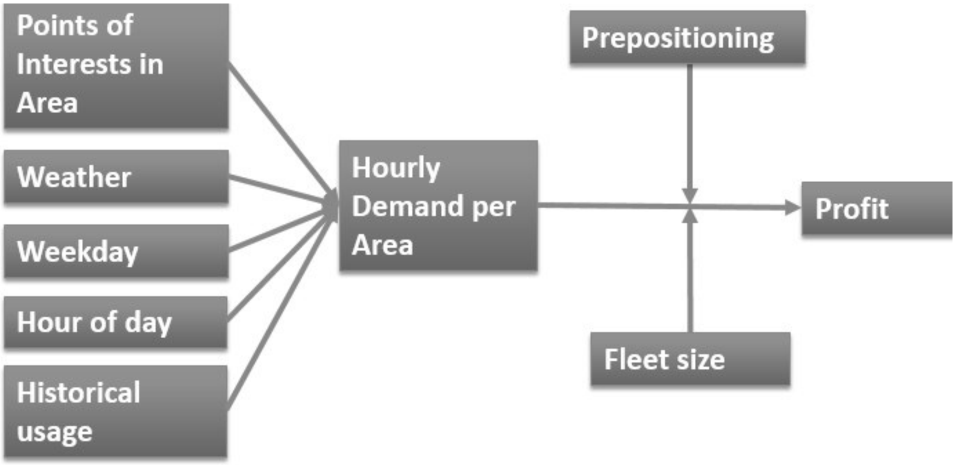

Figure 2.1: Research model that maximizes the profit for one way transportation fleets by repositioning vehicles to areas of high expected demand.

2.3 Model

In this section we present our model of repositioning. Our goal is to match the vehicle demand with vehicle availability by repositioning vehicles based on predicted demand, allowing fleet owners to improve service levels while, potentially, maintaining smaller fleets at lower cost. This repositioning serves as an instrumental goal to validate a generic model to predict mobility demand in urban areas over time. Predicting demand is the fundamental goal and contribution of this paper, as it can be used in many more application areas such as for example zonal mobility pricing. We predict demand per time interval (in this case one hour) and area based on variables related to points of interest in an area and their ratings on Google, typical demand on weekdays and the hour of the day, as well as historical usage of the vehicles, such as the transitions between areas for the given time intervals. For an overview of our research model, see Figure 2.1.

We partition the city into hexagonal tiles, where one tile is an area, as illustrated in Figure 2.2 for tiles with a diameter of 10,000 feet. This is more suitable for the repositioning of vehicles than zip codes or quadrants as used in previous research (Kahlen et al., 2014; Wagner et al., 2015) because in a hexagonal grid every tile has the same distance to all its adjacent tiles. Tile size is flexible in our model. Flexibility is important as when tiles become too big they become meaningless for decision

Figure 2.2: We partition a city into hexagonal tiles as they have the advantage that the distance of a tile to each adjacent cell is the same.

making, but when they are too small, it becomes impossible to make meaningful demand predictions.

Our goal is to maximize profits for one way transportation fleets by repositioning their vehicles in advance to meet expected demand in an area. To profitably reposition vehicles, an accurate demand model is essential to avoid taking away vehicles from tiles where they are needed and avoid moving vehicles to areas where they are not needed. Therefore we have created a model to predict the mobility demand (y) in a given hexagonal tile (h), on a given time depending on the hour of the day (t). Figure 2.3 shows how the rental demand changes spatially and time wise. The darker the hexagonal tile, the more demand was observed at the given time. While the demand between 16-17 hours is concentrated in the city center and Charlottenburg-Wilmersdorf (West), which becomes more pronounced between 17-18 hours, the overall demand decreases and slowly diverts away from the city center towards the districts Reinickendorf and Pankow (North) and Friedrichshain-Kreuzberg (East) between 18-20 hours. This suggests that there are differences in demand over time and space that we can exploit by repositioning vehicles accordingly.

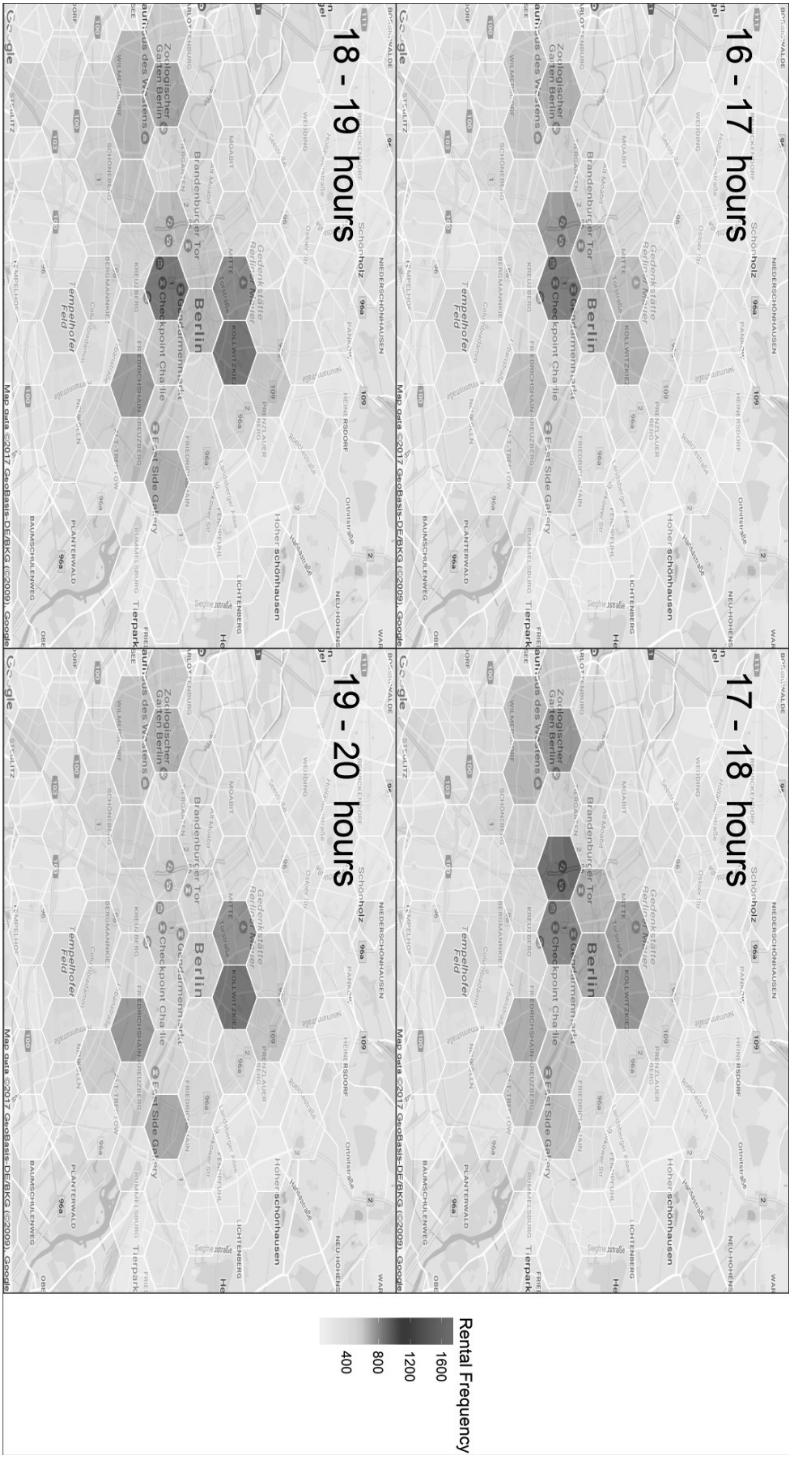

Figure 2.3: Heat map of the rental demand in Berlin. The changing demand over space and time indicates that there is a business case for repositioning vehicles.

We predict the demand per tile and date, based on several indicators. These indicators fall into the categories of weather dependent, point of interest related (with the subcategory of points of interests with a Google rating/price and the number of types of points of interests), and historical usage of vehicles in the tile such as usual demand at this time of the day and the day of the week. In the following we will explain each category of independent variables individually.

Weather: mobility demand depends on the weather. We analyzed how the temperature, the wind, and rain influence the rental demand. For example we expect more rentals when it rains.

Points of interest: the types of points of interest in a tile have an influence on the mobility demand. For example train stations, department stores, or stadiums influence the demand in a different way. Within the point of interest category we differentiate between two types of variables. On the one hand we consider the counts and binaries of each type of interest (i.e. the number of department stores in a tile or whether there is a train station in the tile). On the other hand we also look at the overall percentage of points of interests in a tile that have a rating, whether the average rating in a tile of a type of point of interests is above or below the average rating, and whether the points of interests in a tile have ratings or not.

Historical usage: in contrast to points of interest and weather, historical mobility demand does not give us information on the cause for the rental demand, but is an indicator for latent, unobserved variables and thereby increases the predictive accuracy. This data includes information about the number of vehicles available, which caps the rental demand. It also includes data about historical rental demand in the previous time intervals, and the same time interval on the previous day. Additionally this category includes variables about the incoming and outgoing rental transitions to and from this tile, at the given time and day of the week.

Hour of day and weekday: similar to the historical usage the hour of the day and the day of the week are an indicator for latent variables that positively influence the predictive accuracy of our model. These variables contain information about the average demand at the given tile at this hour and day of the week. In order not to stratify the data, and therefore reduce the sample size, too much we only differentiate between whether it is a weekday or weekend and not between individual days of the week. If we had more data we would differentiate each day of the week separately.

We use a regression model to get an understanding of the important variables. For future work machine learning based models will probably yield even better results. For the notation of our regression model to forecast vehicle demand for a hexagonal tile (h) and time interval (t) and an overview of a sample of the independent variables see Equation 2.1. Note this is only a small selection of the independent variables for illustration purposes. In total there are three weather related variables, l variables related to POI average ratings in a tile, m variables related to POI average prices in a tile, n variables related to counts and binaries of point of interests in a tile, six variables related to historical usage, and 48 variables about the hour of the day and whether it is a weekend or a weekday. We explicitly separate the specific number of variables that do not change across cities such as for example three weather related variables and variable number of variables such as l variables related to points of interest. This makes the model more flexible for future work and comparable across cities, for example in Berlin there may be more (or less) Google types of points of interest than in another city. This is especially important for Google ratings and prices, which we will elaborate on in the next paragraph. These variables give a representative picture of all variables used and give examples of each category of variables. Note that some variables are strongly correlated such as for example shopping mall and department store, however, for predictive models multi collinearity is not an issue (Friedman et al., 2001).

$$
\begin{aligned}
&y_{h,t} = \beta_0\\
&\left.\begin{aligned}
&+\beta_{1.1} Mean.TemperatureC_t\\
&+\beta_{1.2} Mean.Wind.SpeedKm.h_t + \beta_{1.3} Rain_t
\end{aligned}\right\}\text{weather}\\
&\left.\begin{aligned}
&+\beta_{2.1} percentageHasRating_h\\
&+\beta_{2.2.1} aboveAverageRating.store_h\\
&+\beta_{2.2.2} aboveAverageRating.restaurant_h\\
&+\beta_{2.2.l} ..\\
&+\beta_{2.3.1} belowAverageRating.store_h\\
&+\beta_{2.3.l} ..\\
&+\beta_{2.4.1} noRating.store_h\\
&+\beta_{2.4.l} ..\\
&+\beta_{2.5.1} aboveAveragePrice.store_h\\
&+\beta_{2.5.m} ..\\
&..
\end{aligned}\right\}\text{POI in area (ratings)}\\
&\left.\begin{aligned}
&+\beta_{2.6.1} count.store_h + \beta_{2.5.2} count.restaurants_h\\
&+\beta_{2.6.n} ..\\
&+\beta_{2.7.1} binary.store_h + \beta_{2.6.2} binary.restaurant_h\\
&+\beta_{2.7.n} ..
\end{aligned}\right\}\text{POI in area}\\
&\left.\begin{aligned}
&+\beta_{3.1} availabilityPerDay_{h,t}\\
&+\beta_{3.2} rentalsPerDayHourBefore_{h,t}\\
&+\beta_{3.3} rentalsPerDay2HourBefore_{h,t}\\
&+\beta_{3.4} rentalsPerDay24HourBefore_{h,t}\\
&+\beta_{3.5} rentalTransitionsTo_{h,t}\\
&+\beta_{3.6} rentalTransitionsFrom_{h,t}
\end{aligned}\right\}\text{historical usage}\\
&\left.\begin{aligned}
&+\beta_{4.1} we, hour.1_{h,t} + \beta_{4.2} we, hour.2_{h,t}\\
&+\beta_{...} we, hour..._{h,t} + \beta_{4.23} we, hour.23_{h,t}\\
&+\beta_{4.24} wd, hour.1_{h,t} + \beta_{4.25} wd, hour.2_{h,t}\\
&+\beta_{...} wd, hour..._{h,t} + \beta_{4.46} wd, hour.23_{h,t}
\end{aligned}\right\}\text{hour of day and weekday}
\end{aligned}
\tag{2.1}
$$

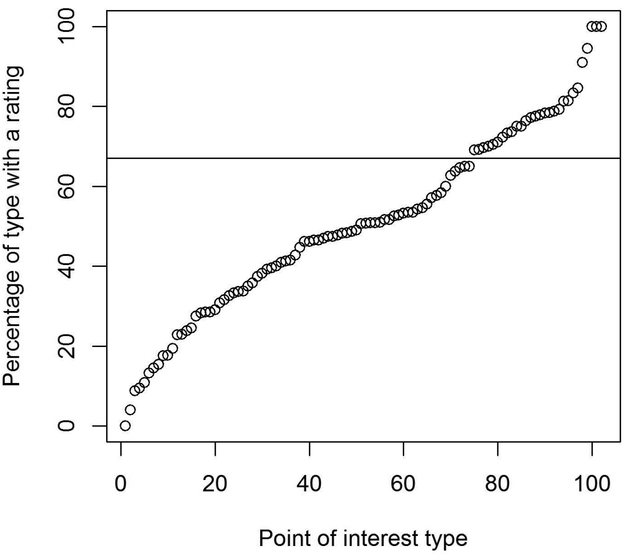

Figure 2.4: There are some points of interest types such as places of worship, or bus stations that do not have a rating. We only consider ratings for types where more than 67% have a rating.

Several types of point of interests such as restaurants frequently have a Google rating and price. However, not all points of interests have ratings and prices such as for example train stations. To avoid having many tiles with missing observations for rating/price we only looked at the average price and rating for types of points of interest that meet the following criteria. Only when a certain threshold of percentage of points of interest per type that have a rating/price is reached we include it in our model. The thresholds are determined by Figure 2.4 for ratings and Figure 2.5 for prices. After the first break between the points we determine the thresholds. The threshold to be included for the average rating/price per type is 67% for ratings (l=28) and 2.5% for prices (m=5).

2.4 Repositioning Algorithm

We reposition vehicles with an assignment algorithm, a constrained optimization that looks at the transactions starting and ending in a given tile at any given point in time. It then takes into account the cost of relocation and the number of cars to move, and the opportunity cost of removing a car from an area where it was needed.

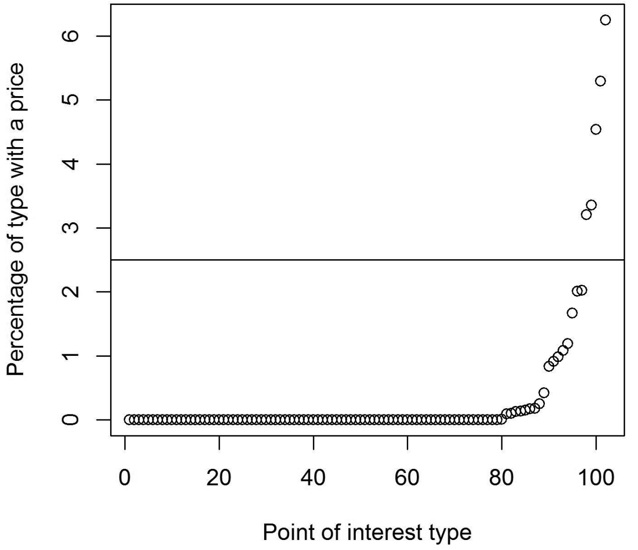

Figure 2.5: There are many points of interest types such as places of worship, or bus stations that do not have a price. We only consider prices for types where more than 2.5% have a price.

This algorithm is a multi-objective optimization. One constraint in the model is fleet size. We look for an optimal assignment conditioned on fleet size. Then we do a series of optimizations (numerical analysis) to find the optimal fleet size. The objective function is to maximize profits (Π) with a dual objective optimization to minimize the fixed cost through the fleet size and to maximize the amount of rental transactions by optimally repositioning vehicles:

$$\arg\max \Pi \tag{2.2}$$

with:

$$\Pi = \sum_{k=1}^{K}(R_k - C_k) - \sum_{i=1}^{I} FC_i - \sum_{o=1}^{O} RC_o \tag{2.3}$$

where R are the revenues of an individual transaction k, C are the cost of an individual transaction k, K is the total number of transactions in the test period/holdout set, FC are the fixed cost per vehicle i, I is the total number of vehicles in a fleet, RC are the relocation cost per relocation transaction o, and O is the total number of relocation transactions in the test period/holdout set.

Conditioned on fleet size, the assignment algorithm moves vehicles from tiles where there are more vehicles than expected demand (*pred.excess*) to tiles where there are less vehicle than expected demand (*pred.shortage*). These are defined as:

$$\text{pred.excess}_{h,t} = \mathit{Vehicles.Available}_{h,t} - y_{h,t} \tag{2.4}$$

$$\text{pred.shortage}_{h,t} = y_{h,t} - \mathit{Vehicles.Available}_{h,t} \tag{2.5}$$

with:

$$\begin{aligned} Vehicles.Available_{h,t} = {} & \mathit{Vehicles.Available}_{h,(t-1)} \\ & + \mathit{avg.Incoming}_{h,t} - \mathit{avg.Outgoing}_{h,t} \\ & + \mathit{relocationsTo}_{h,t} - \mathit{relocationsFrom}_{h,t} \end{aligned} \tag{2.6}$$

where $y_{h,t}$ is the predicted demand from Equation 2.1, $\mathit{Vehicles.Available}_{h,(t-1)}$ are the number of vehicles available at tile h in the previous time interval $t-1$, *avg.Incoming* and *avg.Outgoing* are the average number of vehicles coming into or going out of tile h at the hour and weekday of t, and *relocationsTo* and *relocationsFrom* are the number of relocations brought to tile h and taken from h for period t.

We constructed a relocation array A for each time t that keeps track of the relocation cost RC from cells with excess vehicles to cells with a shortage. The costs are calculated by the relocation cost times the distance between the centroids of the tiles. For an illustration of the relocation array see Figure 2.7. The Figure shows sample data for a relocation array at a specific time interval t. For example it is better to relocate a vehicle from tile 15 to 33 than from tile 15 to 22 as tile 33 needs more vehicles and it is cheaper to relocate vehicles there. Our assumptions are that all vehicles have the same revenue, cost of relocation is linear in distance, and time to relocate is instantaneous.

$$\text{Relocation array: } \mathbf{A_t}[\mathbf{rows}][\mathbf{columns}] =$$

$$\begin{array}{ccccc} \text{from.tile} & \text{to.tile} & \text{relocation.Cost} & \text{pred.excess} & \text{pred.shortage} \end{array}$$
$$\begin{bmatrix} 15 & 33 & 9 & 2 & 3 \\ 17 & 22 & 5 & 3 & 1 \\ 15 & 22 & 17 & 2 & 1 \\ .. & & & & \end{bmatrix} \tag{2.7}$$

The assignment algorithm works as follows. First, it initializes the maximum profit and the optimal fleet size to zero. An important consideration is the proportion of relocation cost to the expected profit for a relocation transaction. This proportion is implemented as a threshold, which is defined by a percentage share of the expected profits of the relocation. The magnitude of the threshold depends on the accuracy of the prediction. With a perfect prediction the relocation cost can be almost as high as the expected profits for this transaction. But in the more realistic case of imperfect predictions, the threshold is lower than the expected profits. The algorithm makes a trade-off between relocation cost and expected profits in the training period. It selects the threshold that maximizes the profits for the fleet in the training period, which is implemented in the function *getPercentageOfExpectedProfitPerRental*(). This function uses the assignment algorithm recursively for the training period to determine the optimal threshold by comparing the profits of all thresholds from 1% to 99% in 1% increments. Then, the algorithm goes through a loop for each vehicle i until it reaches the fleet with size I. The algorithm starts out with an empty fleet and adds a random vehicle i to the fleet. Afterwards, it iterates over all individual time intervals t till it reaches the maximum number of time intervals T. It loads the relocation matrix A for the current time interval t and removes all potential relocations with relocation cost above that threshold from the relocation array. Note that the advantage of a location matrix is that it can be fed with the local conditions of a city such as rivers that increase the distance between several tiles. Then, all rows that do not have a shortage or excess in vehicles are removed. Next, the algorithm enters a while loop that is broken only it the relocation array is empty, or the maximum number of relocations has been reached (the latter is applicable for carsharing only). In the loop, A is sorted based on the vehicle shortage, the vehicle excess, and the relocation cost. After the sorting, the number of relocations possible in the first row are determined based on the lower of the expected shortage and the excess. Once this is done, the vehicles from this row are relocated accordingly form the one tile ($to.Tile$) to the other ($from.Tile$). Then, A is updated to reflect the new excess and shortages in the cells that were changed. Subsequently, the first row of A is removed, and the number of relocations are added to the total vehicles relocated. This is repeated until the while loop conditions are violated. After each time interval iteration the algorithm determines the profits for this time interval at the given fleet size and stores the fleet size and profit as the maximum profits if it exceeds the previous maximum. The algorithm stops when all intervals were considered and the simulated fleet size equals the actual fleet size (i=I). See Algorithm 1 for the pseudocode of the assignment algorithm.

Example: if we apply the algorithm to the sample data from Equation 2.6, one would move two vehicles from tile 15 to 33 and one vehicle from tile 17 to 22. No vehicles are moved from tile 15 to 22 because all excess vehicles from tile 15 were already moved to tile 33, and the vehicle shortage in tile 22 was already covered from tile 17. The total relocation cost would be $\$9 * 2 + \$5 = \$23$. We compare the degree to which we can serve the observed demand and the corresponding profits with and without repositioning of vehicles.

2.5 Data

We collected data in Berlin for the time from the 1^{st} of August - 31^{st} of December 2016. The data includes information about the mobility demand from the free float carsharing provider Car2Go, point of interest data from Google, and weather data from German Weather Services. In this section we will discuss how we have obtained this data and descriptive statistics.

Algorithm 1 Assignment algorithm

```
maxProfit = 0
optimalFleetSize = 0
threshold ← getPercentageOfExpectedProfitPerRental()
for i=1 to I do
    addVehicleToFleet(i)
    for t=1 to T do
        A_t = getRelocationMatrix()
        remove.A_t[rows ≤ threshold][reloc.cost]
        remove.A_t[rows ≤ 0][pred.excess]
        remove.A_t[rows ≤ 0][pred.shortage]
        while length.A_t[rows][] > 0 || total#Relocations ≤ max#Relocations do
            sort(A_t on: pred.shortage, pred.excess, reloc.cost)
            #Relocations = min.(
                A_t[1][pred.excess],
                A_t[1][pred.shortage])
            relocateVehicles(#Relocations, A_t[1][from.tile], A_t[1][to.tile])
            updatePredShortage(A_t[1][from.tile], #Relocations)
            updatePredExcess(A_t[1][to.tile], #Relocations)
            removeRow.A_t[1][]
            total#Relocations ← total#Relocations + #Relocations
        end
    end
    profit_i = getTotalProfit()
    if maxProfit < profit_i then
        maxProfit = profit_i
        optimalFleetSize = i
end
```

2.5.1 Mobility Demand: Car2Go

Daimlers carsharing service Car2Go is particularly suited for this research, as their free float carsharing model entails, that customers can find and rent the vehicles for short amounts of time (minutes to hours) without reservations in an App. The vehicles can be picked up and dropped off at any public parking spot within the operating area defined by Car2Go in a city. Daimler provided us access to the data of their vehicles that are parked. We download this data every 5 minutes and store it in a database. From this data we can infer the rental transactions, whenever a vehicle does not show up in a 5 minute interval, the battery level has decreased, or the location has changed. Therefore the actual rental duration may deviate from our induced rental duration up to 10 minutes, but as the average rental duration is 127 minutes we do not judge it to have a significant influence for the purpose of this study. We also removed all transactions that were longer than 48 hours, as this is the maximum rental duration (18,484 transactions or 6%).We speculate that these transactions are related to maintenance, or moving vehicles to other cities and have therefore no influence on this study. We collected the data from the 1^{st} of August till the 31^{st} of December 2016. For a sample of the induced rental transaction data see Table 2.1.

The average marginal profit per transaction was \$18.29, the average distance driven was 4.7 miles, and the vehicles are rented for on average 127 minutes.

2.5.2 Points of Interest: Google Maps

We obtained the point of interest data from the Google maps API. Google maps API allows to download up to 60 points of interest for a given coordinate and radius. As the number of API calls are restricted we have partitioned the city into a hexagonal grid to minimize the overlap between API calls and the circles they cover. For each hexagonal tile centroid we started an API call with a specified radius. We tried radii of 96, 64, 48 meters. With 96 meters 1.2% of the tiles returned the maximum of 60 points of interest, with 64 meters 0.4% and with 48 meters 0.2%. As a trade-off between speed and completeness we decided to collect Google map data with a 64 meter radius, where approximately 0.4% of the less important points of interest (determined by Google) are missing. We collected the data on the 15^{th} of December 2016. For sample point of interest data see Table 2.2.

In the operating area of Car2Go in Berlin there are 227,896 unique points of interest with 99 different types (n=99) of points of interest, with an average rating of 4.2 on a 5 point scale, and an average price of 1.9 on a 4 point scale.

2.5.3 Weather: German Weather Service

We downloaded the weather data for Berlin in 2016 from the German Weather Service. This data includes the date, the mean temperature, the wind speed, and whether it was raining or not. For sample weather data see Table 2.3. Note that even though the weather data for Berlin is available on an hourly basis for 2016, we use daily data only. This decreases the accuracy of our model. The reason for this is that in future work we would like to compare the models performance to other cities (Amsterdam, Stuttgart, and Copenhagen), where this hourly data is not publicly available.

Berlin had an average temperature of 11 °C in 2016, a mean wind speed of 3.5 km/h, and it rained on 53% of all days.

2.6 Analysis of the Mobility Demand Model

For the purpose of this paper we have chosen a hexagonal tile size with a diameter of 10,000 feet to roughly distinguish between certain areas within a city. While smaller tiles would allow for a more granular evaluation in terms of who would and would not rent a vehicle, the demand predictions gradually lose accuracy. While our model is adjustable to the grid size, we focus on tiles of 10,000 feet for the evaluation. The same counts for the one hour time interval that we look at. The model can be adjusted for narrower and wider time intervals, but for evaluation purposes we fix it to one hour, which gives fleets sufficient time to act on the information, while the information is still relatively recent.

We evaluate the mobility demand model in the setting of a forecasting, time series model with holdout data sets. The validation technique we use is a rolling time window, in which we fit the model with 60 days of data (training period) and predict the upcoming hour (test period/holdout set). We repeat this for all hours in the three month test period from October-December 2016. This yields an average root-mean-square deviation (RMSD) of 1.65, and a mean absolute deviation (MAD) of 1.15. Figure 2.6 shows the convergence of the prediction model and its individual components. The figure shows how the prediction error decreases with longer training periods for the weather, hour and weekday, POI, and historical usage components of the model. It also shows the performance of the combination of all components in

Table 2.1: Rental Transaction Data.

Vehicle	**Time.Start**	**Lat.Start**	**Lon.Start**	**Fuel.Start**	**Time.End**	**Lat.End**	**Lon.End**	**Fuel.End**
GO3482	03.08.2016 12:35	52.55063	13.45735	81	03.08.2016 14:05	52.55056	13.45748	71
GO3482	03.08.2016 15:40	52.55056	13.45748	71	03.08.2016 16:15	52.51073	13.45724	68
GO3482	03.08.2016 16:55	52.50757	13.41498	68	03.08.2016 17:50	52.48951	13.39006	65
..								

Table 2.2: Point of Interest Data.

Name	**Types**	**Rating**	**Price**	**Lat**	**Lon**
Fahrradschmiede	bicycle store, store	3.6		52.4855	13.36332
Museum fur Naturkunde	museum	4.2		52.53057	13.37918
H&M	clothing store, store	3.7	1	52.50795	13.37481
Starbucks	cafe,food, store	3.7	2	52.50794	13.37373
..					

Table 2.3: Daily Weather Data.

Date	**Mean Temperature (°C)**	**Mean Wind Speed ($\frac{Km}{h}$)**	**Rain**
01-01-2016	2	2	0
02-01-2016	-3	6	0
03-01-2016	-10	6	0
04-01-2016	-9	5	0
..			

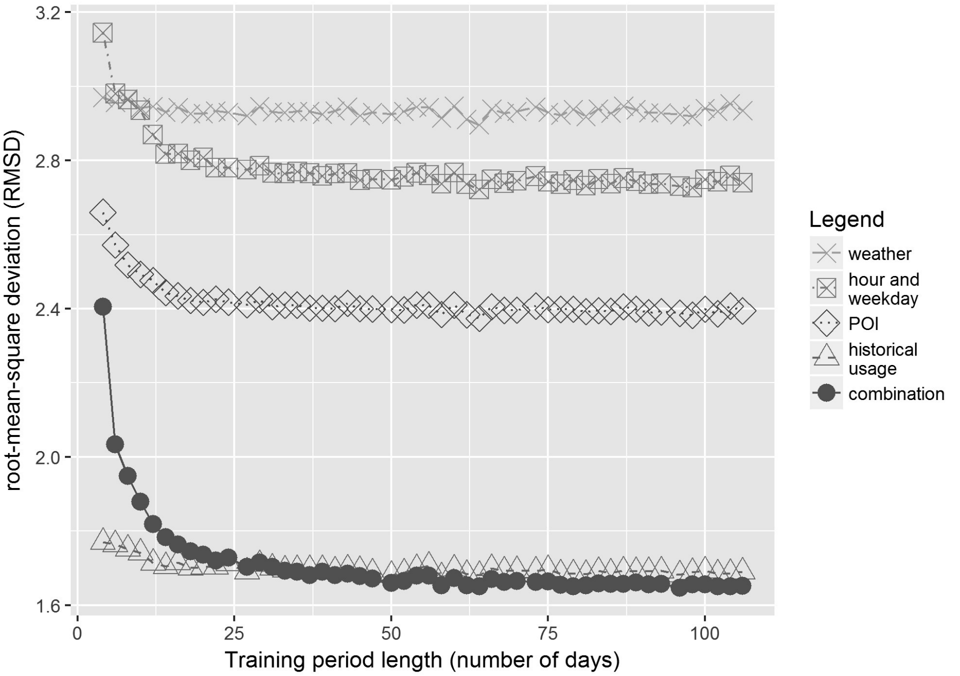

Figure 2.6: Convergence of the various parts of the mobility demand model. The combined model outperforms the historical usage for the first time when the training period is larger than 33 days.

one model. The weather component and the historical usage components need a very short training period (<10 days) only and the error is not reduced much with a longer training period. The POI, and hour/weekday components improve quite significantly given a longer training period (<25 days), afterwards they do not improve much either. Interestingly, the historical usage performs even better than the combined model on a short training period (<33 days). This is because the number of rental transactions in the previous hour are already a good indicator for future performance. However, after 33 days of training period the combined model can learn trends from weather and hour/weekday related components to outperform a model that is based on historical usage only. We use a training period of 60 days as after that point we cannot determine a significant decreases in the error when increasing the training period beyond 60 days.

Similar to Song et al. (2010) we find that there is little variation in the predictability across areas, even though they track peoples mobile phones while we track vehicle movement. The regression model has a good fit with a RMSD of 1.65 with a 60 days of training period. However, we have to validate the effectiveness of the model more thoroughly to be able to make claims about its applied usefulness and what the RMSD of 1.65 actually means. Therefore, we simulated how the decisions of relocating Car2Go vehicles according to our model in Berlin would influence their profitability. Note that we are only aware of observed demand. This entails, that repositioning vehicles in a different way than they were, always results in lower profits because we do not know the additional demand in the new areas with certainty. To bypass this obstacle we reformulate the problem to how we can meet the observed demand with a smaller fleet by repositioning vehicles smartly.

2.6.1 Analysis of the Repositioning Algorithm

In principle the repositioning is a multi-period problem (within the scope of a single day or week from hour to hour). There is an optimization not only in location but in time, so given predicted demand, one might move cars differently and might leave a car underutilized in period one for a better assignment in period two. However, for now we consider only a single period for the relocation for simplicity. In future work we would like to consider the multi-period characteristics of this problem, too, which would increase the profits even further.

We use a training period of 60 days to train our forecast model as described in the previous section to predict the areas with too many vehicles ($pred.excess$) and too few vehicles ($pred.shortage$) and test it on the consecutive hour as a holdout set. Then we evaluate how much a fleet could have earned by repositioning its vehicles given the cost function of a carsharing, a transportation network company, or an autonomous vehicle fleet. This is repeated in a rolling time window for each hour of the test period 1^{st} of October - 31^{st} of December 2016. The optimal threshold for relocations is when the relocation cost are less than 80% of the expected marginal profits of the cell to which the vehicle will be moved.

To simulate the profits of repositioning vehicles, we make the following assumptions: the annual, marginal fixed costs per vehicle (FC) are \$5,000. The relocation cost are linear in distance, $3\frac{\$}{km}$ (includes: relocation employee cost, public transportation back to the city center, vehicle wear and tear) for carsharing, $1\frac{\$}{km}$ (includes: driver compensation and vehicle wear and tear) for transportation network companies with drivers, and $0.5\frac{\$}{km}$ (includes: vehicle wear and tear) for autonomous vehicles. Our assumption that the instantaneous relocation time is reasonable for a one hour time interval in the operating area in Berlin, but may need to be included as a constraint for larger operating areas or smaller time intervals. Our model is easily adaptable

Table 2.4: Confusion (error) matrix: The matrix shows the accuracy of repositioning decisions during the test period for carsharing.

	Predicted	
Actual	**Do nothing**	**Reposition**
Do nothing	3,977,150	2,729
Reposition	24,473	8,448

to set the distance to the tiles that are not reachable in one time horizon to infinity so that they are not considered. For simplicity we also assume that all vehicles have the same marginal profits even though we see patterns over tiles and time such as one-way or round trips that have varying marginal profit levels, which we would like to include for future work. For now we assume that each rental earned \$18.29, which is the average marginal profit per transaction.

In total the simulation has to make relocation decisions for each hour of the 152 days of the training set for each vehicle. In most cases the algorithm decides to leave the car where it is. In some of these cases, it would have been more more profitable to reposition these vehicles to another area. However, when the algorithm decides to reposition vehicles it is correct in 76%. For a confusion matrix that shows the number of right and wrong decisions for carsharing fleets, see Table 2.4. In sum, we find that by repositioning vehicles according to our model, fleets can increase their profits by up to 6.8%. Figure 2.7 shows the marginal profits from repositioning vehicles and how they change when the fleet size changes. The three lines represent the cost functions for relocations of carsharing (dotted line), transportation network companies (dashed line), and autonomous vehicles (solid line). While the magnitude of the marginal profit increases due to repositioning differs, the shape of the graph is similar for all three relocation cost functions. Initially, when there is much more mobility demand than vehicle supply, relocating vehicles is not very sensible because they are needed everywhere and relocating them only adds relocation cost. However, as more vehicles are added to the fleet to serve demand, repositioning is very beneficial. The marginal profits of repositioning vehicles peak at 23%, 24%, and 31% of the total fleet size for autonomous vehicles, transportation network companies, and carsharing companies respectively. After these peaks the marginal profits for all three types of

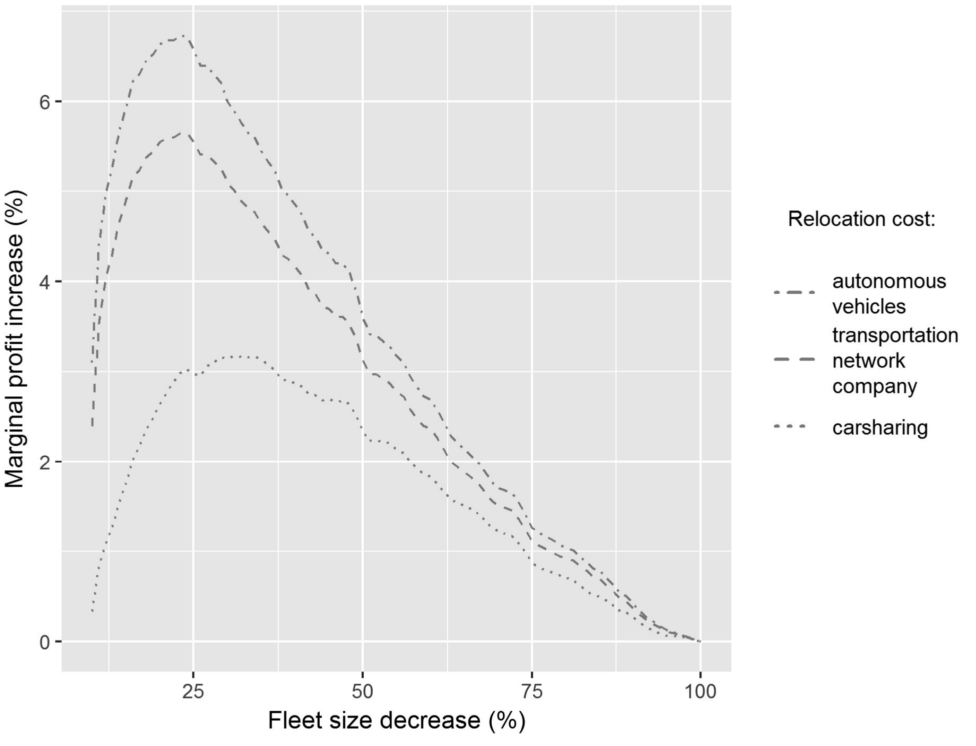

Figure 2.7: The marginal profits of repositioning vehicles in our data are limited by the observed demand. We bypass this problem by serving the same observed demand with a smaller fleet.

relocation cost tail off and reach zero when the fleet size reaches the real fleet size due to the observed demand problem in the data described above. The benefits of repositioning vehicles vary between 3% and 7% depending on the relocation cost. Note that the relocation costs for the different mobility providers can also be interpreted as a sensitivity analysis of the relocation cost.

However, these additional benefits only make up for a certain proportion of the total profits. Figure 2.8 shows a breakdown of the earnings split up in revenues, cost, and profit. The cost increase linearly with the minor exception of the relocation cost. The revenues increase exponentially initially and have a knee at around a fleet size of 50% where revenues remain approximately stable. The profits for all relocation cost functions and the baseline scenario without repositioning vehicles peak at 51%, which is a fleet size of 561 vehicles. This immense fleet size reduction potential stems from a low fleet utilization; on average vehicles are utilized 20% of the time. By reducing the fleet size and smartly positioning the fleet, we increase this number to 44%. However, one has to be careful in interpreting this number. It means that in a one shot game it is most profitable to have a small fleet size and cover the maximum demand with it. However, customers may also want to have the service available of having a car in an area that is underutilized and may use the service less in response to such a drastic fleet size reduction. Regardless of the repositioning the optimal fleet size is smaller than the actual fleet size. This either suggests that the fleet is currently too large and therefore underutilized, or that the hexagonal tiles are too big. As the data supports the hypothesis of a low utilization rate of 20% we leave the investigation of various hexagonal tile sizes up to future research. This means for the fleet that either they should reduce their fleet - unless they have business goals that are not related to profitability related to for instance a growth strategy to acquire more customers. This analysis shows that the prediction model to predict the mobility demand in various areas throughout the city is reliable and can be used for decision making such as for example relocating vehicles to higher demand areas.

2.7 Conclusions and Future Work

Increasing the utilization of vehicles can make mobility more affordable. Free float carsharing services, transportation network companies with drivers or even autonomous vehicles attempt to leverage increased utilization to offer cheaper mobility. We have built a model to predict the demand for mobility in an urban setting. This helps to relocate vehicles from less demanded areas and position them in areas of high demand, which changes over time. It is difficult to compare our findings to previous work as previous work did not reduce the fleet size. While Kek et al. (2009) found an idle time reduction of 13%, Wagner et al. (2015) found a reduction of 16%, we are able to reduce idle time by 120%. However, these values have to be compared and interpreted carefully. By reducing the fleet size to serve the same observed demand, we show that profits increase, however, the total revenues decrease by 5%.

The goal of this study was to maximize fleet profits by repositioning vehicles, which also reduces the needed fleet size, by relocating from low to high demand areas. We have evaluated our model with a fleet of 1,100 carsharing vehicles in Berlin and conducted an analysis into what happens when we repositioned these vehicles according to our model. Therefore we partitioned the city into hexagonal tiles, which have the advantage that each tile has the same distance to all adjacent cells, and predict demand for each tile over time. We predicted the demand by taking the

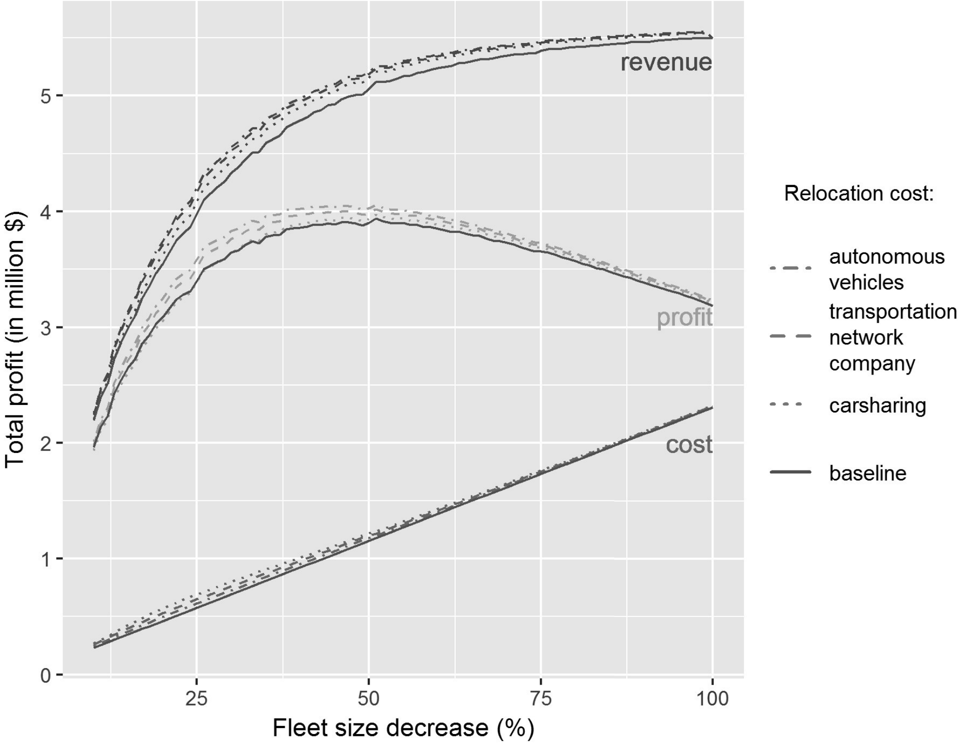

Figure 2.8: Overview of the revenue and cost structure of a fleet with various relocation cost. It is striking that regardless of the fleet type (autonomous vehicles, transportation network, or carsharing) the maximum profits are achieved with a fleet size of 51% (561 vehicles).

weather, points of interests and their ratings, historical usage, and the time of the day and day of the week into account. We show that using this demand prediction model and an assignment algorithm to reposition vehicles can be profitable for fleets. We also show that with the respective relocation cost functions for carsharing a 3% profit increase, for transportation network companies with drivers a 6% profit increase, and for transportation companies with autonomous vehicles a 7% profit increase is possible.

While we have illustrated the usefulness of mobility demand prediction at the hands of a repositioning problem, this can also be used in other areas such as the prediction of availability of electric vehicles in vehicle-2-grid applications, where electric vehicles provide electricity to the grid when needed (Kahlen and Ketter, 2015). Another area of application could be pricing models for mobility that depend on time and location.

In this research we have analyzed a reduction in fleet size to deal with unobserved demand. Another way in which we intend to deal with the unobserved demand in future work is to get demand data from competitors as it has been done by Padmanabhan et al. (2006). We have therefore started to collect data from the carsharing service DriveNow in Berlin to analyze how a fleet could outperform its competitor by smartly repositioning their vehicles. We also intend to look at and compare this analysis to other cities where Car2Go offers their carsharing services such as for example Amsterdam. Finally, we would like to investigate the sensitivity of the results to the size of the hexagonal tiles in future research.

Chapter 3

FleetPower: Creating Virtual Power Plants in Sustainable Smart Electricity Markets [1]

3.1 Introduction

Carsharing is increasingly becoming a popular business model (Firnkorn and Müller, 2011) where cars are rented for short durations (sometimes minutes). Unlike traditional car rentals, where renters keep possession of the car even during the long unused hours, the idea of carsharing is to rent the cars for short, one way trips. Many of the

[1] This paper is currently under peer review at a journal in the 1^{st} round.
Parts of this chapter appear in the following conference proceedings:
Kahlen , M.T., Ketter, W., Gupta, A. (2017). Electric Vehicle Storage Management in Operating Reserve Auctions. *In Proceedings of the 50th Hawaiian International Conference on System Sciences.* Hawaii, United States (4-7 January 2017).
Kahlen, M.T. & Ketter, W. (2015). Aggregating Electric Cars to Sustainable Virtual Power Plants: The Value of Flexibility in Future Electricity Markets. *In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI-15).* Austin, United States: Association for the Advancement of Artificial Intelligence. (25-30 January 2015).
Kahlen, M.T. & Ketter, W. (2015). FleetPower: An Intelligent Trading Strategy to Form Virtual Power Plants in Sustainable Smart Energy Markets. *In Proceedings of the Conference on Information Systems and Technology.* Philadelphia, United States (31st of October-1st of November)
Kahlen, M.T. & Ketter, W. (2015). Using Electric Vehicle Fleets as Sustainable Virtual Power Plants: Evidence from a Real-World Setting. *2015 Winter Conference on Business Intelligence (WCBI).* Snowbird, United States (12-14 March 2015).
Kahlen, M.T., Ketter, W. & Dalen, J. van (2014). Using Electric Vehicle Fleets as Sustainable Virtual Power Plants: Evidence from a Real-World Setting. *24th Workshop on Information Technologies and Systems.* Auckland, New Zealand (17-19 December 2014).

carsharing companies use electric vehicles (EV) as their carsharing fleets. Clearly, while the cars are parked the carsharing companies incur investment and maintenance costs. While this loss is unavoidable for traditional fossil fuel based cars, for fleets with EVs additional revenues can be generated by appropriate use of EVs as virtual power plant (VPP), a collection of distributed power sources that are centrally coordinated by an information system (IS) to offset energy imbalances (Pudjianto et al., 2007). In this paper, we develop and validate a method to increase the utilization and hence the profits of electric vehicle (EV) carsharing fleets. Our approach allows EVs to charge when there is a surplus of electricity and discharge it to the grid (vehicle-2-grid, V2G) when there is a shortage of electricity. We develop a computational control mechanism for the VPP to decide how the EVs should be allocated over time in terms of charging, discharging, and being available for rental customers. Based on a discrete event simulation model that is calibrated using real data on availability of vehicles and their movements in three distinct locations supplemented with data on electricity prices on reserve markets, we show what extra profits can be generated from EVs in addition to the rental business, by participating in these electricity auction markets. In essence, we develop *smart markets* (McCabe et al., 1991; Gallien and Wein, 2005; Bichler et al., 2010) to enable energy sources to be deployed cost-effectively. Fleets can offer the storage on short term electricity markets. They can chose between the day-ahead, intraday, and operating reserve market based on the largest price differentials. In this research we seek to analyze the operation in control reserve market, which acquires back-up power sources that can consume electricity from or dispatch electricity to the grid within seconds. These back-up sources guarantee an alternative source of power when another power source produces more or less then had been promised (for example, due to technical defects or weather-related issues). The fact that EV batteries can be charged, and discharged flexibly makes them very suitable for offering control reserve power at economic rates. However, the findings in this paper are therefore a conservative estimate of actual profits, as we only look at the price differentials in one markets.

To operationalize our model, we compute trading prices (bids and asks) for every 15-minute time interval of a given week to charge and discharge EVs and these prices are offset against the opportunity costs of not renting out the EV. We have develop an intelligent software agent (Collins et al., 2010), called *FleetPower* which combines information from the location, the state of charge of the battery (SoC), historical rental transaction data, and historical prices on the control reserve market and uses this information to make optimal allocation of EVs to either the rental market or a

VPP (charging or discharging). The agent considers both the profits from charging and discharging and what effect the withdrawal of vehicles for rent might have on the mobility of those wanting to hire cars (sociotechnical implications). This means that our model makes an explicit trade-off between the asymmetric benefits to be gained from either offering cars for rental or using them to balance the grid in real time. To generate profits for the fleet, the system optimizes the allocation of EVs either to those needing to rent an EV (the social part) or to the balancing market which purchases services to balance the grid (the technical part). The focus is on ensuring that the availability of EVs for rental is not compromised, as the opportunity cost of loosing a rental customer is very high. While the profits from renting out a vehicle are on average around $15 per transaction, profits from the charging and discharging are only a few cents per 15 minutes. As a consequence FleetPower offers the VPP capabilities conservatively.

We use real data from EV carsharing fleets and control reserve markets to test our strategies via a simulation platform that allows us to calibrate the trading prices. The actual data on electric vehicle carsharing fleets was provided by Daimler's subsidiary, Car2Go. Car2Go is a city carsharing service where customers can rent cars, which they pay for on a per-minute basis. To use the service users have to register and pay a one-time registration fee. Once registered, they can make use of the freefloat service which enables them to pick up and drop off vehicles anywhere within the city boundaries, not necessarily in the same location. The service is available in 30 major cities in North America and Europe, with a total of more than 13,000 Smarts ForTwo. We tracked the location, state of charge, and transactions of 500 EVs in Stuttgart, 300 in Amsterdam, and 300 in San Diego for 14 months. These cities have 220, 1,500, and 100 charging stations respectively. The high number of charging stations in Amsterdam is related to government incentives. Users get 10 minutes' free driving if the state of charge is below 20% when they return the EV to the charging station. We also use the prices of the control reserves from the transmission system operators of the corresponding regions (Transnet BW, Tennet, and California ISO).

We show that carsharing fleets can increase their gross profits without compromising the mobility of rental customers. This result is consistent across all three cities. Profitability depends on whether there is an appropriate charging infrastructure and on the level of market demand for the control reserves that are available. We find that the largest profit increases for the VPP come from payments made for charging EVs when there is surplus energy that needs to be removed from the grid. Our data shows that the market rarely uses the EV batteries to cover electricity shortages, due to the high cost of batteries. However, both discharging and charging the EVs contributes to the bottom line of carsharing fleets. In the case of Stuttgart in particular, it is very profitable for the fleet; the profits from the VPP cover the cost of all the electricity used by their customers. Even with relatively low penetration of these vehicles at present, one of the benefits of the VPP that can immediately be realized is that carsharing fleets do not have to pay anything to fuel their EVs. In the future these cost reductions may be even more substantial as the demand for back-up power increases, due to the growing adoption of volatile, sustainable energy sources (Agricola, 2014).

Our research derives synergies by using EVs in the control reserve market instead of conventional, fossil-fuel-based means of peak-balancing, thereby creating greater efficiencies across the system. Renewable energy sources are weather-dependent and their production is difficult to forecast. Large-scale penetration of volatile energy sources poses a challenge to the stability of the grid (Kassakian and Schmalensee, 2011). The grid is the backbone of a highly perishable electricity supply chain, where supply and demand have to be in balance at all times. With the phasing out of power plants based on fossil fuels and a growing number of renewable energy sources, balancing the grid becomes increasingly difficult. In practice, this means that the chance of blackouts increases, with potentially disastrous consequences. Our research provides insights on how electric vehicles (among other energy sources) can be used to mitigate the instability of electric grids caused by the increasing amount of renewable resources. A key contribution of this research is that it increases the supply in the operating reserve markets, and therefore decreases the market price.

Mak et al. (2013) and Avci et al. (2015), who have been studying the location of battery-switching stations, consider future work on the area of intelligent charging of EV batteries as a crucial step in moving towards a sustainable economy. In the IS research community Watson et al. (2010) recognize the societal importance of the issue addressed in this paper by formulating an energy informatics framework with the aim of creating an ecologically sustainable society. Their framework formulates the need for IS research to take on the role of managing supply and demand in an energy-efficient way, and we show that we can do this by using EVs as mobile energy resources that are coupled by an information network that monitors the location, charging status, rental demand, and electricity supply and demand to create a real-time decision framework for optimizing resource utilization and profits. While forward looking, this topic is already receiving attention from the automotive industry. For example, Tesla Motors cars have a function to charge at cheaper night-time tariffs. With the Internet-of-Things the framework could be used not only in cars but also in individual appliances and devices (Porter and Heppelmann, 2014). An example is Google, which acquired Nest Labs with its programmable smart thermostats that produce energy savings of between 10% and 15% (Nest Labs, 2015). Creating appropriate IT infrastructure is central to the coordination mechanism for the current industrial examples as well as for the mechanism we propose.

To the best of our knowledge, this is the first study that uses real driving, charging, and locational data from more than 1000 EVs and makes an international comparison among three major cities in the USA, the Netherlands, and Germany with different energy mixes. Another key contribution of our research (from the perspective of EV balancing research) is that we assume that driving patterns are unknown a priori; this represents a key characteristic in EV balancing research, as previous work in this area by Vytelingum et al. (2011) and Tomic and Kempton (2007) was done using stationary batteries and EV fleets with known driving schedules respectively.

3.2 Background and Related Literature

This section summarizes relevant, previous research and outlines the general setting of balancing renewable energy sources. First, we describe the electricity market in detail explain how the trading prices are computed. Subsequently, we will position our work within the information systems literature on EVs, the carsharing context, and sustainability in general.

3.2.1 Balancing the Electrical Grid: Control Reserve Market

Electricity is sold on day-ahead and intraday markets as unit commitments hours before it is physically generated. However, when a source cannot meet its commitment (for example, due to technical problems or weather related issues) there are control reserve markets to guarantee immediate replacement (known in the US as the real-time market, and in the EU as the secondary control reserve market). These reserve markets require extremely fast reaction times called ramping rates from participating generators. For an overview of these markets and how they differ in their ramping rates, see Figure 3.1. EVs possess large electrical batteries whose energy is almost instantly accessible without ramping cost, making them very suitable for reserve purposes. The present study focuses on the secondary control reserve market with a required ramp rate of 30 seconds (International Grid Control Cooperation, 2014). We focus on this market because the energy prices are higher than in markets which

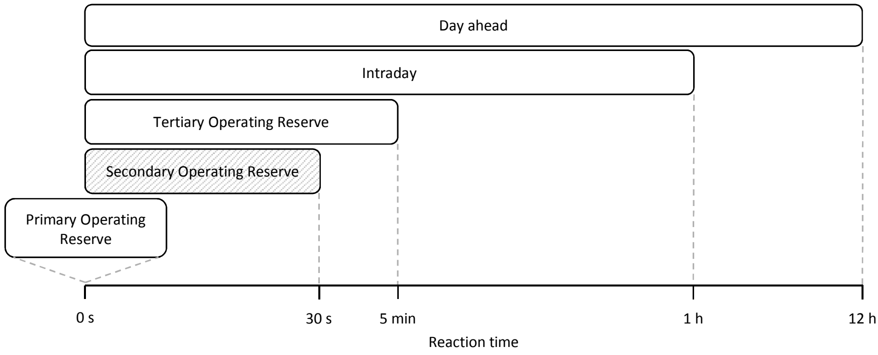

Figure 3.1: The reaction time, which is the time between notification and generation, differs according to the market. With no ramp-up time, EVs are able to comply with the short reaction times on the primary and secondary reserve markets.

allow for a slightly longer ramp-up time. From this point on, when we are referring to energy markets we refer to the secondary control reserve market.

In the control reserve market, power plants are paid to be on standby so that they can produce (or consume) electricity when needed. The market is coordinated by electronic auctions, in which participants make *asks* or issue *bids*. The clearing mechanism is a multi-unit, first-price, sealed-bid auction, which is settled on a "pay-as-bid" basis (International Grid Control Cooperation, 2014). 'Asks' refer to the generation of electricity at short notice (*up regulation*), while 'bids' relate to the consumption of electricity, also at short notice (*down regulation*). Asks to generate electricity and bids to consume electricity state the price for which they would either generate or consume electricity and the maximum quantity they could generate or consume a week in advance. The transmission system operator settles these asks and bids as needed 30 seconds before delivery in merit order (the cheapest resources are used first).

We assume that in the future bids and asks can be placed separately for each 15-minute time interval. This future state is desired by TSOs to reduce entry barriers renewable energy sources to operating reserve markets (Agricola, 2014). This is a trend that is already see implemented partially today. Traditionally, the tender period was monthly, up till now it was weekly, and from 2017 onwards it is going to be daily with 4 hour intervals. We are therefore confident that in the future 15 minute intervals are realistic given the trend to automated trading in the electricity sector.

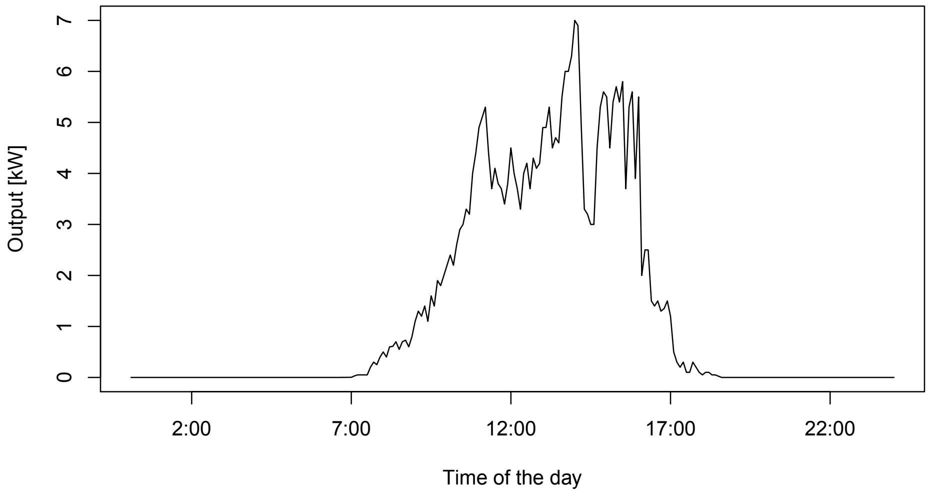

Figure 3.2: Solar panel electricity output illustrating the erratic behavior in photovoltaic electricity production with extreme variations in output. Data from Minneapolis, Minnesota in April 2015.

This market setup has implications for market power and competition. For a detailed discussion about this threat see Knaut et al. (2017).

Increasing levels of intermittent renewable energy and the decommissioning of conventional power plants exposes the control reserve market to the risk that at some point the demand may exceed the available supply (for instance, when the sun is suddenly covered by cloud and photovoltaic cells stop producing energy). Figure 3.2 provides an example of electricity output from solar panels, showing how production from solar panels is erratic, with extreme variations in output per minute. Note how the panel produces its maximum output at 1.30 pm, yet only minutes later production drops by more than 50% - in stark contrast to fossil fuel generators that produce electricity at a constant rate. These drops in energy output need to be offset within seconds to avoid blackouts.

3.2.2 Information-based Sustainable Society: Carsharing with Electric Vehicles

Information systems can be both a contributor to climate change and way of dealing with negative environmental impact. Similar to Loock et al. (2013)'s use of information to align individual interests with sustainability, we use information to align organizational goals with sustainability by means of a decision support system. As a result, financial and environmental goals are brought into harmony to foster carbon neutrality (Malhotra et al., 2013). Knowing when and where people rent EVs puts EV fleets in a position to make inferences about the rentals patterns of the population, and to make sociotechnical trade-offs (Geels, 2004) between their need for transportation and the need for storage on the energy market. We demonstrate this trade-off in a simulation platform similar to the one described by Ketter et al. (2016b,a) and calibrate it using real-world data.

Charging many EVs in the same neighborhood at the same time can quickly overload transformers and substations (Kim et al., 2012; Sioshansi, 2012). Previous research has addressed this issue by proposing smart charging, meaning that EVs are charged at times when the grid is less congested, helping to complement peaks in electricity consumption without creating new peaks. With smart charging EV fleets are given financial incentives to change their charging times, resulting in significant reductions in peaks (Valogianni et al., 2014b). The departure times of EVs parked at public charging stations in California, Kara et al. (2015) show that an intelligent scheduling would result in a reduction of 24.8% in the monthly energy bill for users. An extension of smart charging is the V2G concept[2]. There are many successful models that use stationary storage to participate in electricity markets such as for example Mashhour and Moghaddas-Tafreshi (2011) or (He et al., 2016). Mashhour and Moghaddas-Tafreshi (2011) has built a model to bid in both energy and operating reserve markets. However, He et al. (2016) has done the same but included battery life cycles, which is an important consideration. We also consider battery life cycles, but additionally look at the unavailability of vehicles due to rentals, which adds an additional layer of complexity. A study by Vytelingum et al. (2011) considers the savings a household can make with a battery exposed to dynamic pricing on the energy wholesale market, and finds that efficient use of the battery would provide savings of 14% in utility costs and 7% in carbon emissions. Similar effects are found by Zhou et al. (2015) in an industrial setting. Another study relating to EVs finds yearly benefits per EV of $176-203 (Schill, 2011). Tomic and Kempton (2007) show that the profitability depends on the target market: the larger the variations in the electricity price, the higher the profitability. Therefore, we focus on the control reserve market from Section 3.2.1.

[2]Vehicle-to-grid (V2G) discharging is technically possible. Even though not all charging stations support discharging yet, the standard of the International Electrotechnical Commission IEC 62196 supports V2G. For the purpose of this study, and with regard to future infrastructure, we assume that all charging stations have V2G capabilities.

Most studies make the assumption that households or car owners trade on the energy wholesale market. This assumption is not realistic, because they do not have a sufficient quantity of electricity to sell or buy to meet the minimum lot sizes required to participate in the market. To address this issue, Ketter et al. (2013) introduced the notion of electricity brokers (a.k.a. aggregators), which act on behalf of a group of households in order to reach the minimum lot size requirements. Simulations by Brandt et al. (2017) and Kahlen et al. (2014) show that this is possible to achieve with EVs. On top of the brokers we also apply the concept of a VPP. The asks and bids that are accepted constitute a promise to deliver electricity to the market, but which specific source will be used to fulfill that promise is not decided until actual delivery (i.e., whether a commitment will be delivered specifically from EV A or B (or a combination) is decided in real-time, based on the availability of those particular vehicles). We will show that this is a powerful tool which carsharing fleets can use to offer appropriate service levels for rental customers while making additional profits from balancing markets.

As the number of charging stations increases EVs are more likely to be connected to the grid and to be used as part of a VPP. As we want to make a statement about the profitability of VPPs of EV in the future, we also need to consider the possible density of charging infrastructures in the future. In earlier articles in this journal, Mak et al. (2013) and Avci et al. (2015) put forward an an optimal spatial infrastructure design for battery-swapping stations. This set-up has also been studied by Wolfson et al. (2011b). However, we focus on conventional charging stations instead, because although there are 1,820 charging stations in Stuttgart, Amsterdam, and San Diego combined, there are no battery-swapping stations. We will therefore make recommendations on where additional charging stations should be placed.

A shortcoming of the existing studies is that - with the exception of Kara et al. (2015) - they all used either small fleets or data from combustion engine vehicles which have a longer range and are not subject to 'range anxiety', the fear becoming stranded with an empty battery. More importantly, in previous research, trips are assumed to be known in advance. In reality trips are more spontaneous (nondeterministic) and not always known in advance. This is problematic when an EV is committed to either charge or discharge at the same time as someone needs to drive it. Here a sociotechnical trade-off needs to be made between balancing the grid (technical) and providing mobility to customers (social). As it is impossible to determine precisely what value each individual places on mobility, we approximate its value with the profits from rental transactions. Free float carsharing, where users can pick up and drop off the vehicle anywhere allows us to specify the value for mobility for all pick up and drop off locations and times. Firnkorn and Müller (2011) show that free float carsharing has a significantly positive environmental effect, reducing carbon emissions by 6%. The optimal dimensions of the area where carsharing vehicles can be picked up and dropped off was studied by Wagner et al. (2016). For our study a free float carsharing business model fits very well as rentals are paid on a per-minute basis, and there still is uncertainty about where and for how long people will rent an EV (rentals are not booked in advance, i.e. they are nondeterministic), an issue which has not been covered in previous studies.

Previous research proposed the use of EV capacity as control reserves (Vytelingum et al., 2011; Schill, 2011), but it has not yet been shown whether this might be useful in a business setting. We show its usefulness not only in a realistic setting with 1,100 EVs, but also make an international comparison across the United States, the Netherlands, and Germany. Furthermore, our research can be generalized to all VPPs, and not just VPPs from EVs. Our model can be parametrized to represent different types of storage with different ramp rates. See Table 3.1 for an overview of the related literature.

3.3 Data

The fleet of Car2Go consists of 500 EVs in Stuttgart, as well as 300 EVs in both Amsterdam and San Diego. In addition to a sign-up fee, members pay for the carsharing service on a use basis only (per minute/hour/day, with an extra per km fee above a threshold of 50 km in Amsterdam and Stuttgart or 150 miles in San Diego). The prices across locations are similar but not identical (see Table 3.2), so we will use the arithmetic mean of the prices for ease of comparison between locations.

We chose Car2Go because it is a carsharing fleet with a global presence which uses the same cars (Smart ForTwo) across locations, thus allowing for a good comparison between countries. The sites are particularly suited for the purpose of this research because they are heterogeneous in terms of their energy mix. California and Germany are both at the forefront of renewable energy penetration and standards, while the Netherlands rely on a more conservative electricity supply based on fossil fuels .

The rental and driving data was retrieved from a private application programming interface which we were given access to by Daimler. We retrieved a list of all EVs that were available for rental at the time of the query from the Car2Go website, `www.car2go.com`. We downloaded the data, added a time stamp, and stored it in a

Table 3.1: Overview of related literature: Previous literature did not consider that driving patterns are not always known in advance and have not made an international comparison.

Author	Real Data	Smart Charging	Vehicle-2-Grid	Virtual Power Plant	Charging Point Placement	Carsharing	Nondeterministic Driving Patterns	International Comparison
Avci et al. (2015)					✓			
Brandt et al. (2017)	✓	✓	✓	✓				
Firnkorn and Müller (2011)	✓					✓		
Kahlen et al. (2014)		✓	✓	✓				
Kara et al. (2015)	✓	✓						
Ketter et al. (2013)				✓				
Kim et al. (2012)		✓	✓					
Mak et al. (2013)					✓			
Pudjianto et al. (2007)				✓				
Schill (2011)		✓	✓					
Sioshansi (2012)		✓						
Tomic and Kempton (2007)	✓	✓	✓					
Valogianni et al. (2014b)		✓	✓					
Vytelingum et al. (2011)		✓	✓					
Wagner et al. (2016)	✓					✓		
Wolfson et al. (2011b)					✓			
Zhou et al. (2015)		✓	✓					
FleetPower	✓	✓	✓	✓	✓	✓	✓	✓

Table 3.2: Environmental variables for Car2Go.

Description (variable, unit)[1]	**Stuttgart**			**Amsterdam**			**San Diego**		
EV type					Smart ForTwo Electric				
Max. battery capacity (Ω, kWh)					16.50				
Battery depreciation cost (D,$\frac{\$}{kWh}$)					0.13				
Charging speed per EV (γ,kW)			$\leftarrow$		3.60 (linear)		$\rightarrow$		
Discharging speed per EV (δ,kW)					3.60 (linear)				
Charging efficiency (ξ^{charge},%)					96.00 [2]				
Discharging efficiency ($\xi^{discharge}$,%)					97.40 (Reichert, 2010)				
EV fleet size (I)			491			343			367
Charging stations			1381			3561			541
Industrial electricity tariff (ET,$\frac{\$}{kWh}$)			0.12			0.10			0.10
Rental fee per minute ($)			0.37			0.39			0.41
Rental fee per hour ($)			18.92			18.92			14.99
Rental fee per day ($)			74.93			87.63			84.99
Extra fee after 50 km ($\frac{\$}{km}$)			0.37			0.39			0.45
	Min	**Avg**	**Max**	**Min**	**Avg**	**Max**	**Min**	**Avg**	**Max**
EVs available	148	395	491	64	253	343	106	281	367
EVs at charging station	32	104	232	21	70	122	2	34	64
Rental revenues (RB,$)	4	17	134	4	15	133	4	18	133

[1] Exchange rate is 1 Euro = 1.34 U.S. dollars.
[2] Value unknown, assumption based on our best estimate and talks with industry experts.

database every 15 minutes from May 1, 2014 to June 29, 2015; we were also continuing to collect the data for future research. This information contains the unique car name, the geographic coordinates of where the car is parked, the street name and zip code of that location (l), the state of charge of the battery (SoC), the state of the interior and exterior, and whether the EV is currently charging. We infer certain information about the transaction, such as how long the EV was rented, how many kilometers were driven, and how much revenue was earned as rental benefit ($\widehat{RB}$) by looking at the duration and timing of when the EV was unavailable for rent and the difference in the SoC level beforehand and afterwards. Even though the number of kilometers that can be covered using average fuel consumption will depend upon individual driving behavior, and this could therefore affect the accuracy of our estimates, we are confident that the differences will in fact be marginal, since all the journeys take place within the same urban environment. We assume that a fully charged EV will cover a distance of 66 miles (106 km). See Table 3.3 for an extract from the raw data and the information that we infer from it.

A drawback of the data set is that there is a chance that a car may be returned and rented again to another customer within the 15-minutes time interval. However, for the sake of our analysis, the EV remains unavailable, so this does not have a significant influence on the overall estimation and results. We also observe that several times particular EVs did not feature in the data for more than two days, even though the maximum rental duration is 2 days. We speculate that these cars were either in maintenance, repair, or not able to drive for some other reason, and were therefore not shown as available by Car2Go. We therefore removed from the dataset all rentals which we inferred from the data to have lasted more than two days. For a graphical illustration of how the rentals are distributed over a city see Figure 3.3, which shows the annual rental density in Amsterdam.

We infer the location of charging stations based on the GPS coordinates of where cars have been charged at least once in the dataset. We assume that if a car is parked at a charging station, it will be connected to the charging station. This is a sound assumption, because cars are only allowed to park at a charging station when they are plugged in, and any car that does not comply with this may be towed away.

3.4 Model Description

At the core of this research is the development of a decision support system that places bids and asks in a market. The market's clearing mechanism ultimately decides

Table 3.3: This is an extract from the raw data. From this data we infer that a customer drove 7 miles (12km), rented the EV for 45 minutes, and paid \$14.99 (tariff for a full hour).

Car ID i	**Time** t	**State of charge** q	**Latitude**	**Longitude**	**Interior**
Car#1	12.05.2014 17:00	71%	32.76393	-117.122	good
Car#1	12.05.2014 17:15	71%	32.76393	-117.122	good
Car#1	12.05.2014 18:00	60%	32.76556	-117.168	good
..					

Exterior	**Street**	**Zip code** l	**City**	**Charging**	**Engine**
good	Felton St 4728	92116	San Diego	false	electric
good	Felton St 4728	92116	San Diego	false	electric
unacceptable	Fashion Valley Rd 1261	92108	San Diego	false	electric
..					

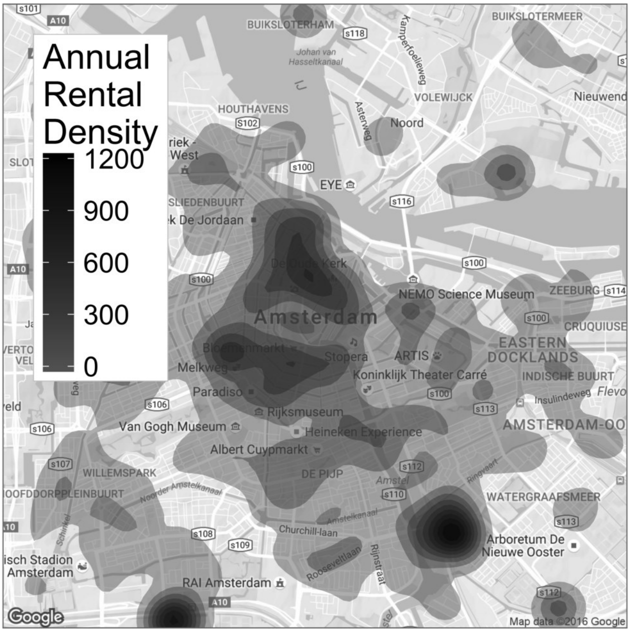

Figure 3.3: Shows where rentals occur most frequently in Amsterdam. The city center (middle), and business districts Zuidas (south west) and Amstel (south east) have particularly high densities of rental transactions.

when to turn EVs into VPPs. The system is evaluated in a simulation environment bootstrapped with real-world carsharing driving data from Car2Go. A discrete event simulation is most suitable for this purpose, as we are dealing with a complex system that would be prohibitively expensive to build in the real world and where market parameters would be difficult to manipulate. In the following sections, we outline our selected approach and the reasoning behind it.

3.4.1 Virtual Power Plant Decision Support: FleetPower

Fleets need to decide how to deploy EVs by deciding which ones should be charged, which should provide V2G services, and which should be made available for rental, and they then bid accordingly. Figure 3.4 provides an example of how EVs are allocated in San Diego. The charging and discharging (V2G) is physically constrained to EVs that are connected to a charging station. Making real-time deployment decisions in this complex environment requires automated decision-making by an intelligent trading agent (Collins et al., 2010). We call this intelligent trading agent, which acts on behalf of the fleet, *FleetPower*. How FleetPower bids for the charging and discharging energy of the electric vehicles is described in the activity diagram in Figure 3.5. The agent needs to submit asks and bids for whatever price it is willing to charge or discharge and to decide how many EVs it wants to make available. The asks and bids need to be placed before the auction closes, and after the auction the agent has to provide or consume whatever quantity of energy has been agreed for any accepted bids or asks. The first step ❶ for the agent is to forecast the total amount of energy stored and how much can still be stored in the EVs that are available (parked at charging stations) for the timeslot under consideration. Next ❷, the agent has to determine a price at which it would be willing to sell or buy energy, to at least cover the opportunity cost. Afterwards ❸, this information about the price and the SoC of the EVs forms the basis of the asks and bids to be submitted to the auction. After the asks and bids have been submitted to the auction the market decides which asks and bids to accept and reject according to the pay-as-bid mechanism. The fleet needs to make sufficient EVs available to match the quantity of energy that has been agreed. ❹ These are dedicated EVs that deliver or consume energy according to the accepted asks and bids. ❺ If a customer asks to rent one of these particular EVs, either ❻ another car connected to a charging station then replaces that EV in the VPP in order to deliver the agreed amount to the market, or ❼ the customer is told that no car is available and ❽ the potential revenues are written off as opportunity cost. In practice customers will not be turned away as these cars will not show up on the list of available EVs, so customers would not notice any difference, especially since this is done already for cars that are charging. Note, that if another EV was free in the immediate vicinity, it was assumed that this car would then be rented out instead. Our interpretation of immediate vicinity is that customers are likely to be willing to walk to another car if it is approximately 250 meters away (drawn from a normal distribution with mean of 250 meters and standard deviation of 100 meters (d)). This value seems realistic to us, but we have also tested a mean of 100 and 500 meters with no significant difference in results. The great-circle distance between the coordinates is calculated using the haversine formula (Robusto, 1957). For a graphical illustration of the walking distance, see Figure 3.6. In the next section we will explain each step of the bidding procedure in more detail.

3.4.1.1 Determine Ask and Bid Quantity ❶.

The first step in the ask and bid submission is to determine the quantity of electricity that should be offered in each 15-minute time interval. While it is important for customers to rent a car at a specific location, the precise location within a city is

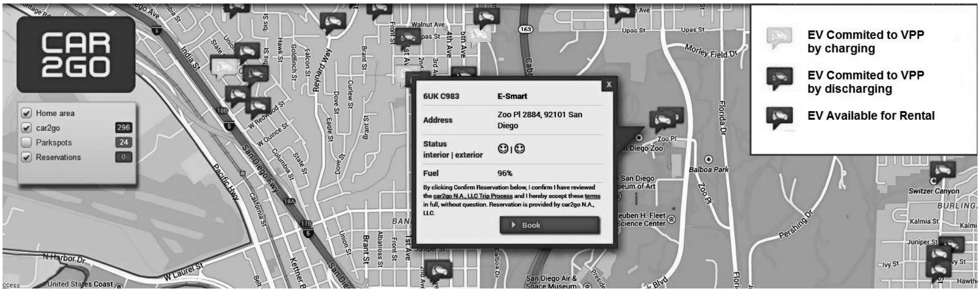

Figure 3.4: EV's from Car2Go in San Diego, USA. FleetPower committed strategically placed EV's as virtual power plants to charge or discharge (V2G).

less relevant for energy markets as long as the car is parked at a charging station on the same distribution grid. Rather than making a decision on how each individual EV should be deployed, we can estimate an overall quantity of energy to charge and discharge, which allows us to harness the 'risk pooling effect'. This effect refers to the fact that EV storage potential and energy stored can be predicted more accurately for a whole fleet rather than for each individual EV. It is easier to make an accurate estimate of the number of cars that will be rented out in Amsterdam on a Sunday between 5.00 pm and 5.15 pm than to predict which specific EVs will be used.

For the purposes of this study, we have applied various machine learning algorithms, including neural network regression, support vector machine regression, and random forest regression, in order to forecast the energy storage available for charging (Q_t^{charge}) and discharging ($Q_t^{discharge}$) for the whole fleet at a specific time. We chose these regression algorithms because we use many attributes and there is a dependency in the data between the independent and dependent variables.

At the end of every week, the market closes for submissions for all the 15-minute intervals of the following week. We are therefore interested in predicting storage availability for up to one week in advance. The capacity to store or discharge for the fleet of EVs as a whole is predicted using the following equations:

$$Q_t^{charge} = \beta_{t,0} + \beta_{t,1} * day\_of\_week(t) + \beta_{t,2} * hour\_of\_day(t) \tag{3.1}$$

$$Q_t^{discharge} = \beta_{t,0} + \beta_{t,1} * day\_of\_week(t) + \beta_{t,2} * hour\_of\_day(t) \tag{3.2}$$

where β_0, β_1, β_2 are unknown parameters. The decisive factors determining the availability of storage are the day of the week (day_of_week), and the hour of the day in 15-minute intervals (hour_of_day). To predict the energy storage for each week we

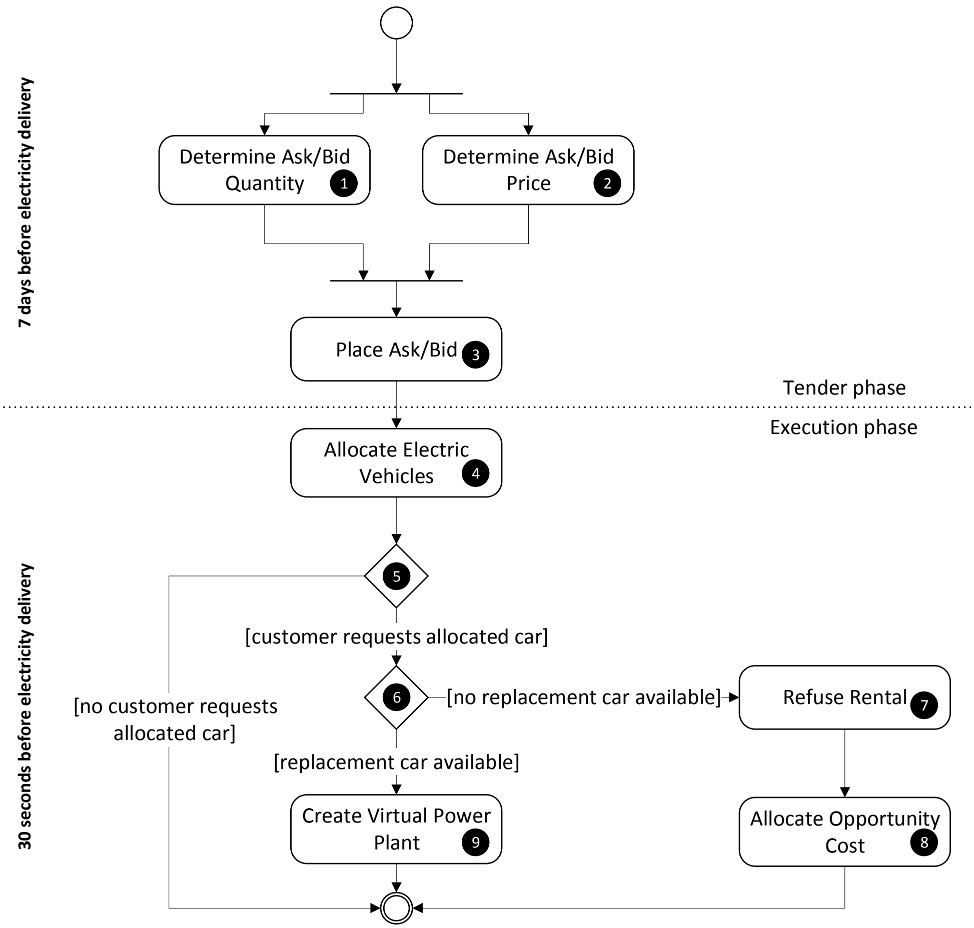

Figure 3.5: Activity diagram showing the decision-making steps involved in FleetPowers bidding on the secondary control reserve (real-time) market for energy.

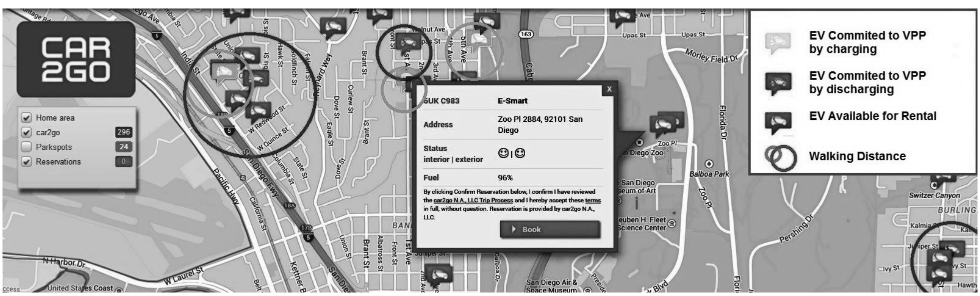

Figure 3.6: EVs from Car2Go in San Diego, USA. The circles indicate people's willingness to walk if the car they wanted in the first place is not available.

use a fixed two months time period (training period) to learn the daily and weekly patterns. The training period duration is fixed so that all predictions are comparable. The duration of the training period will be discussed in more detail in Section 3.5. A random forest regression model had the highest accuracy of prediction during the training period. This model was parametrized with two randomly preselected variables (mtry=2), 1000 randomized trees, and a minimum sum of weights for splitting of 5. We do not consider time series models, because commitments are due one week in advance. Special events such as soccer games, elections, or national holidays, and their influence on the model, will be discussed in Section 3.6.3.

In its essence the issue we are dealing with is a classification problem. We have to decide how many EVs we should assign to which class (rental or VPP). However, there is an asymmetric pay-off between assigning EVs to certain classes. Renting earns the carsharing fleet \$17.61 on average per transaction and the VPP earns the fleet \$0.09 on average per transaction. In addition, asks and bids on the energy market are binding and non-delivery will result in very high penalties. We therefore give misclassifications for the rental class proportionally more weight than the VPP class. This weight is assigned with the stratified sampling method, where we sample disproportionately to reflect the asymmetric pay-off (Berk et al., 2009). This method decreases the likelihood that our model adds a car to a VPP.

Example: Assume, for instance, that we are interested in submitting a bid in Amsterdam for Sunday, July 6, 2014 for the time interval t 5.00 pm to 5.15 pm (t=60 as it is the 60^{th} 15-minute interval). To predict the available storage we look at the training period from May 1, 2014 to the day on which asks and bids can be submitted for auction on June 30, 2014. Based on the number of EVs and their state of charge for each Sunday in that time period, as well as each t=60 time period, we predict the availability for the test period July 6, 2014 at t=60. To account for changes in usage patterns over time we explicitly include the availability between t=60 of the last Sunday as a lagged dependent variable (in this case: June 29, 2014). With more historical data one could also include the same day from previous years to improve the accuracy of the model. If there were on average 10 EVs connected to charging stations, each with a state of charge of 70% (SoC) and a 16.5kWh battery (Ω), the storage available for charging would be $Q_t^{charge} = 10 * 0.3 * 16.5kWh = 99kWh$, and the storage available for discharging would be $Q_t^{discharge} = 10 * 0.7 * 16.5kWh = 231kWh$. Due to physical constraints of the available infrastructure in Stuttgart, Amsterdam, and San Diego, the charging (γ) and discharging speed (δ) of 3.6kWh per hour (or 0.9kWh in 15 minutes) and charging (ξ^{charge}) and discharging efficiencies ($\xi^{discharge}$)

of 96% and 97.4% limits the actual values to a maximum of $10 * 0.9 * 0.96 = 8.6kWh$ and $10 * 0.9 * 0.974 = 8.8kWh$, rather than 99kWh and 231kWh for the 15-minute interval.

3.4.1.2 Determine Ask and Bid Price ❷.

The second step in the ask and bid submission process is to determine the price at which the asks and bids should be offered so as to balance out potential gains to be made from the auction versus the likelihood of the offer being accepted. There is a price for capacity (standby fee) and for electricity (per unit of energy). We bid at a capacity price of $0\frac{\$}{MW}$ to ensure that our bids will always be considered by the System Operator.This also makes the strategy independent of whether or not a capacity price will be applied in the future with shorter time intervals. We show that the bidding strategy at $0\frac{\$}{MW}$ is economical even if there is a capacity price component, but the claim of optimality does not apply if there is a capacity fee. To determine the electricity price we apply a bottom-up model which estimates the optimal price per EV. For each EV, the fleet has a number of costs that need to be covered. For example, when charging an EV, the agent needs to ask a price P^{charge} that takes into account the alternative, which would be simply paying the industrial electricity tariff, the opportunity cost of being unable to serve a customer while charging, plus a margin. To discharge the EV (V2G), an agent should ask a price $P^{discharge}$ that is based on the energy cost of charging in the first place, the cost of battery depreciation, the opportunity cost of not being able to serve a customer while discharging, and of not being able to serve customers in the future due to a lower battery SoC, plus a margin.

For a table of notation, including measurement units, see Table 3.4.

Determine the price for charging (P^{charge}): EVs can be parked anywhere in the city, but only if an EV is parked at a charging station does FleetPower have the option to turn it into a VPP. Where this is the case, FleetPower can bid in the energy market for a cheap electricity rate. Bids are submitted to the auction, and Figure 6 shows the components of the bid, together with the bid quantity and price. The first component of the bid price, opportunity benefit, serves as a reference point; FleetPower will not purchase electricity on the energy market if the industrial electricity tariff were cheaper. The second component, the expected gross profits from rental, ensures that EVs are less likely to charge when it is probable that they will be rented out. The industrial electricity tariff, and the expected rental profit determine the break-even point at which renting out or turning an EV into a VPP

Table 3.4: Table of notation.

Variable	Description	Unit
$\widehat{RB}$	Expected rental benefit per unit of energy stored	$\frac{\$}{kWh}$
RB	Observed rental benefits	\$
C^{charge}	Charging cost, see Equation 3.3	\$
$C^{discharge}$	Discharging cost, see Equation 3.6	\$
c	Rental probability, see Figure 3.8	$\frac{\%}{100}$
D	Battery depreciation cost	$\frac{\$}{kWh}$
d	Distance EV_i to closest EV available for rent	km
EC	Energy cost, based on P_t^{charge}	$\frac{\$}{kWh}$
ET	Industrial electricity tariff (flat price)	$\frac{\$}{kWh}$
I	Total number of EVs	
i	Specific EV	ID
l	Location	zip code
P	Bid/ask price for buying or selling electricity from reserve market	$\frac{\$}{kWh}$
Q	Bid/ask quantity for buying or selling electricity from reserve market	kWh
Q^*	Equilibrium quantity (sign indicates shortage or surplus electricity)	MWh
q	State of charge (SoC) (Ψ/Ω)	$\frac{\%}{100}$
t	Time interval	index
β	Unknown regression parameter	-
Δt	Duration of a time interval	0.25 hours
γ	Charging speed	kW
δ	Discharging speed	kW
λ	Dummy to account for opportunity costs from recharging	boolean vector
μ	Margin on the bid/ask price, to optimize the bidding price	$\frac{\$}{kWh}$
ξ^{charge}	Charging efficiency	$\frac{\%}{100}$
$\xi^{discharge}$	Discharging efficiency	$\frac{\%}{100}$
Ψ	Amount of electricity stored in an EV	kWh
Ω	Maximum battery capacity	kWh

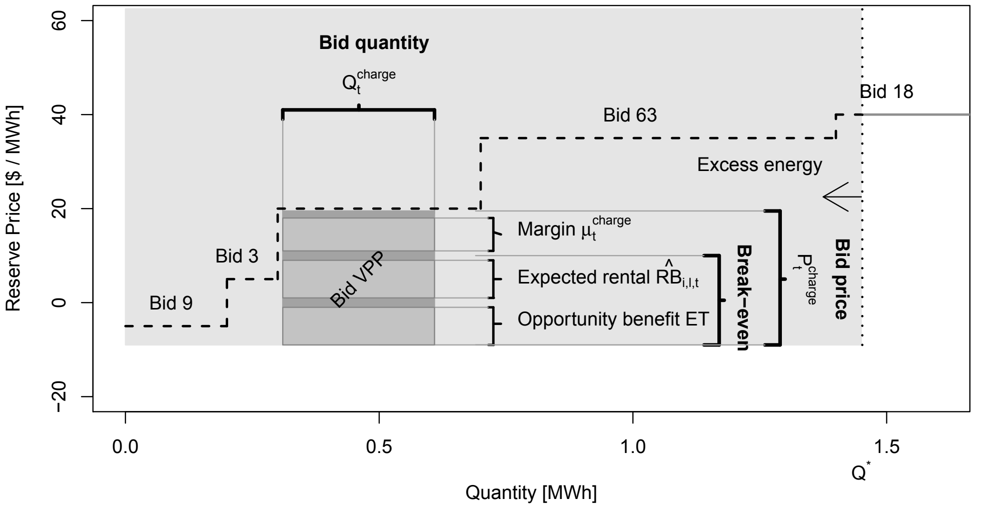

Figure 3.7: The graph shows the demand curve for getting rid of surplus energy; in this example the grid needs to get rid of 1.45 MWh. As our VPP bid offers to consume this electricity more cheaply than bid 18, which is the last (partially) cleared bid, the market agrees to sell 0.4 MWh to the fleet.

are equally matched financially. The final consideration, the margin, allows the fleet to make a profit, and here a trade-off needs to be made between the pay-off and the likelihood of the bid being accepted. This margin parameter optimizes the profits for the fleet owner based on the probability of being called upon in the training period to maximize profits. We now describe the bid in more detail.

The financial cost of charging (C^{charge}) a specific EV i at 15-minute time interval t is determined by the following equation:

$$C^{charge}_{i,l,t} = \frac{\min(SoC_{i,l,t} * \Omega, \delta * \Delta t)}{\xi^{charge}} \left(-P^{charge}_{i,l,t}\right) \tag{3.3}$$

where $min(SoC_{i,l,t} * \Omega, \delta * \Delta t)$ is the amount of electricity that could still be charged to the battery of car i at interval t and (P^{charge}) is the bid price to charge, which differs per EV i and time interval t. The variable ξ^{charge} accounts for the charging inefficiency.

The bidding price P^{charge} for charging is determined as follows:

$$P^{charge}_{i,l,t} = ET - \widehat{RB}_{i,l,t} - \mu^{charge}_{t} \tag{3.4}$$

where ET is the opportunity benefit of not having to pay the industrial electricity tariff, $\widehat{RB}$ is the expected rental benefit which we will describe next, and μ^{charge} is the profit margin which is parametrized to maximize the overall profits for all previous time intervals t (of the training data set). In other words, we take the electricity tariff, we deduct what we could have earned with the EV if it had been available during that period, and we add a margin to arrive at the lower electricity price the carsharing fleet would be willing to accept in return.

We use the same machine learning algorithms to predict the rental profits per unit of energy and thus to decide how much energy to offer (see ❶ in Figure 3.5). In contrast to the quantity prediction, support vector machine regression had the best predictive accuracy for rental profits (see ❷ in Figure 3.5). The rental profits are predicted with the following equation, similar to Equations 3.1 and 3.2:

$$\widehat{RB}_t = \beta_{t,0} + \beta_{t,1} * day\_of\_week(t) + \beta_{t,2} * hour\_of\_day(t) \tag{3.5}$$

The support vector machine regression was parametrized using a radial basis kernel function with the parameters gamma = 2 and cost = 1. The expected profit for renting EV i per unit of energy ($\widehat{RB}$) during interval t parked at location l is determined by a support vector machine regression with four independent variables: rental probability c, state of charge of the battery SoC, interior status, and exterior status.

The rental probability c captures the preferences and behaviors of those who rent EVs. The probability has three dimensions: location, the hour of the day, and the day of the week. The locational dimension gives insights into the likelihood that EVs are rented out given that they are parked in a certain district, which is represented by a zip code. The temporal dimension gives insights into the likelihood that EVs will be rented out given a certain hour of the day and a day of the week. We break time down into discrete 15-minute intervals for each day of the week. Based on this information, we create a four-dimensional model that enables us to predict whether a car is likely to be rented out within the next 15-minute interval, based on the day of the week, the specific 15-minute interval, and the zip code of the place where the car is parked. Unlike day and time, zip code is a categorical variable. Figure 3.8 provides an example from the city of Amsterdam, which serves as an input to the support vector machine regression model used to predict the rental transactions. There are significant differences between locations: for example, on a Sunday morning in Amsterdam in zip code 1012 (central train station) the rental likelihood of 5 to 10% is much higher than in zip code 1014 (periphery), where the likelihood is below 1% .

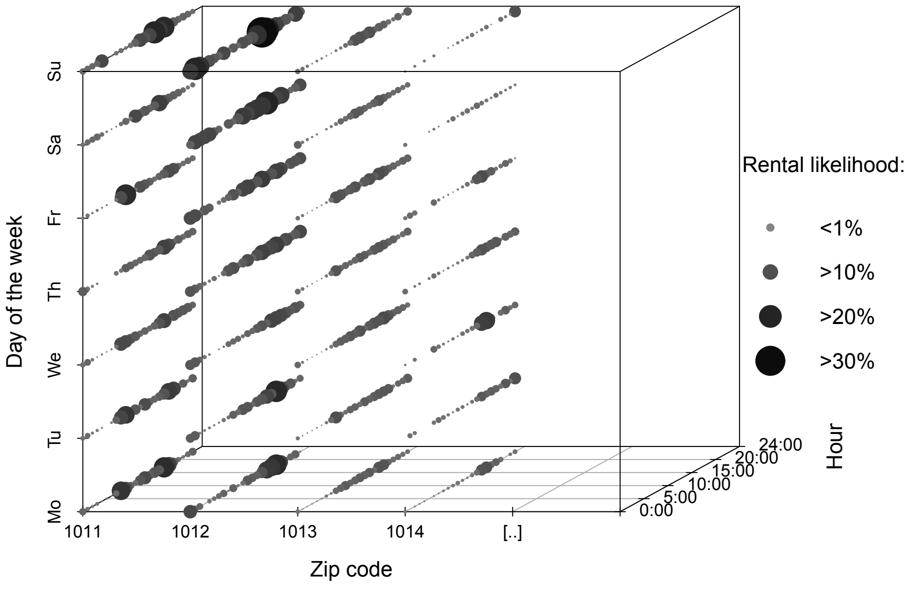

Figure 3.8: Four-dimensional rental likelihood model that shows when EVs are rented out in Amsterdam, based on the day of the week, hour of the day (15-minute interval), and zip code of where they are parked. There is a distinct difference in rental likelihoods - for instance, between the central station (1012) and the periphery (1014).

Example: How we determine the bid price for charging is illustrated by what happens with car $ID\#5$ on the morning of Monday May 11, 2015 between 5.15 am and 5.30 am. The battery is charged (SoC) to 90%, the interior and exterior status are "good", and the car is parked in zip code (l) 1012 (Amsterdam central station). At this time and location the likelihood of the car being rented out is below 0.3%, and the trained support vector machine regression over the training period (60 days: April 11, 2015 to May 11, 2015) predicts an expected rental benefit of $0.042\frac{\$}{kWh}$ (over the kWh left in the battery). Given an industrial electricity tariff of $0.08\frac{\$}{kWh}$ and an optimal margin of $0.02\frac{\$}{kWh}$, the bidding price is $P^{charge}_{5,1012,21} = 0.08\frac{\$}{kWh} - 0.042\frac{\$}{kWh} - 0.02\frac{\$}{kWh} = 0.018\frac{\$}{kWh}$. If the quantity $Q^{charge}_{5,1012,60} = 0.9kWh$ is bought from the market, and an adjustment is made for efficiency losses ξ^{charge}=0.02, the total opportunity cost of charging the EV during that period would be $C^{charge}_{5,1012,60} = (0.9kWh/(0.98)) * (0.08\frac{\$}{kWh} - 0.018\frac{\$}{kWh}) = \$0.057$. In order for the charging of this EV to be economical during this 15-minute interval, the carsharing fleet would need to bid at a price not exceeding \$0.057. If it would pay more for electricity it would be better off to use the flat electricity tariff. Any figure above this would mean that the fleet would be better off charging its vehicles using electricity supplied at the standard flat tariff.

Determine the price for discharging/V2G ($P^{discharge}$): An EV can also contribute to a VPP by discharging if it is parked at a charging station with V2G. FleetPower then has the option to sell electricity through V2G by submitting an ask to the energymarket. Figure 3.9 shows an ask quantity and ask price, broken down into its various components, and compares these to other asks in the auction. The first component of the ask price (energy cost) is the sum needed to reimburse the fleet for the cost of charging the EV in the first place. The second component, battery depreciation, compensates the fleet for wear and tear on the battery. The third component, the expected rental gross profit, ensures that the maximization takes into account that an EV is less likely to discharge using V2G when it is probable that it will be rented out, and this calculation includes an allowance for the time needed to recharge the EV to its previous charge state. Even though rental gross profits also include an element to cover the costs of battery depreciation, we explicitly include this as a separate part of the ask price, because there are substantial differences between discharging and driving in terms of the battery depreciation depending on the volume of activity. For example, at night the expected battery depreciation costs from rentals are close to zero, because it is unlikely that someone would rent an EV, whereas if the ask is accepted, the battery depreciation costs associated with discharging

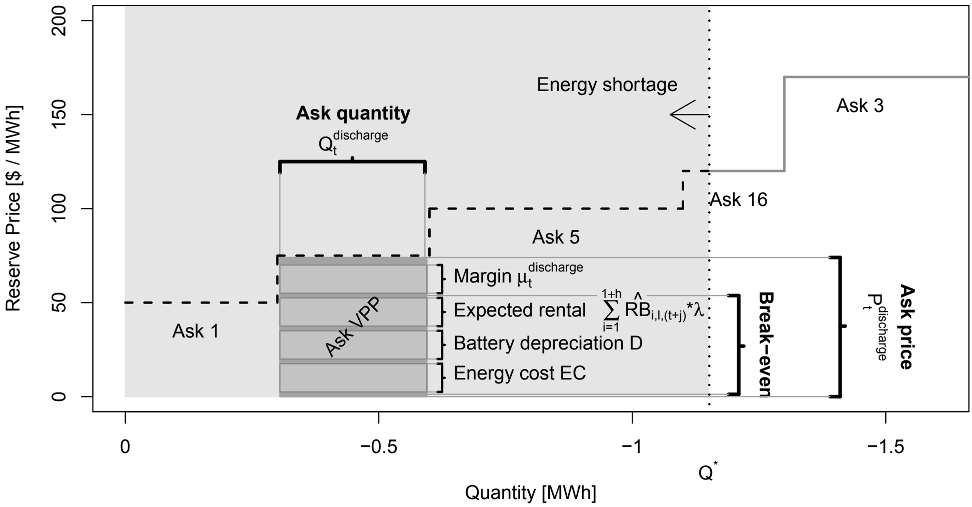

Figure 3.9: The graph shows the supply curve for the purchase of energy to bridge a deficit in the grid; in this example, an additional 1.2 MWh is required. As our VPP ask offers to provide this electricity more cheaply than ask 16, which is the last (partially) cleared ask, the market agrees to buy 0.3 MWh from the fleet.

and subsequent recharging will be incurred in full. Also, in this case the electricity cost, the battery depreciation cost, and the expected rental profits are combined to determine the break-even price at which the rental and VPP are of equal value to the carsharing fleet. The last consideration, the margin, allows the fleet to make a profit in the "pay-as-bid" market, though a trade-off needs to be made between the potential gains and the likelihood of the ask being accepted. We describe the ask in more detail below.

The financial cost of discharging ($C^{discharge}$) a specific EV i at 15-minute time interval t is determined by the following equation:

$$C_{i,l,t}^{discharge} = \frac{Q_{i,l,t}^{discharge}}{1 - \xi^{discharge}} \left[-P_{i,l,t}^{discharge} \right] \tag{3.6}$$

where ($Q^{discharge}$) is the electricity stored in EV i that can be accessed within time interval t. $P^{discharge}$ is the price at which the electricity is being offered for sale, as defined in Equation 3.7. $\xi^{discharge}$ is the discharging inefficiency that accounts for energy conversion losses.

The asking price for discharge ($P^{discharge}$) is determined as follows:

$$P_{i,l,t}^{discharge} = -D - EC - \sum_{j=1}^{1+h} ((\widehat{RB}_{i,l,(t+j)} * \lambda_{i,l,(t+j)}) - \mu_t^{discharge} \tag{3.7}$$

where the cost for wear on the battery is depreciated (D) for each kWh of energy used. Also, the energy costs for charging EC, based on the asks accepted during the training period, are taken into account. The summation term refers to recharging the EV after V2G. $h = \text{round}\left(\frac{Q_{i,l,t}^{discharge}}{\delta * \Delta t}\right)$ is the time it takes to recharge the EV, rounded to the nearest time interval (15 minutes). $\widehat{RB}$ are the opportunity costs of not being able to rent out the EV due to it being committed to a VPP during the current interval t and costs of recharging it subsequently. The dummy variable λ states that opportunity costs only apply if the next person to rent the vehicle cannot complete the expected trip $\widehat{RB}_{i,l,t+j}$ with the remaining capacity from V2G. $\mu^{discharge}$ is the margin which maximizes the overall profits for the time intervals t in the training data set in a similar way to the margin in Equation 3.4.

Example: To see how we determine the bid price for discharging, take the example of car $ID\#5$ on the morning of Monday May 11, 2015 from 5.15 am to 5.30 am at zip code 1012. The same conditions apply as in the example provided above for charging. Assume that the battery depreciation are $D = 0.1\frac{\$}{kWh}$, the quantity in question is $Q_{5,1012,60}^{discharge} = 0.9kWh$, the discharging speed $\delta = 3.6kW$ per EV, the rental benefit for the next time interval (5.30-5.45 am) is $RB_{5,l,61} = 0.055\frac{\$}{kWh}$, and $\lambda_{5,l,61} = 1$ as there are rental costs in t=60, but as the battery SoC is completely full it is unlikely that in period t=61 the EV will have too little battery power left to be used for another rental. Under these circumstances the price for discharging can be expressed as follows: $P_{5,1012,60}^{discharge} = -0.1\frac{\$}{kWh} - 0.08\frac{\$}{kWh} - \sum_{j=1}^{2}((\widehat{RB}_{5,l,(60+j)} * \lambda) - 0.02\frac{\$}{kWh} = 0.018\frac{\$}{kWh}$. If the quantity $Q_{5,1012,60}^{discharge} = 0.9kWh$ is bought from the market, and an adjustment is made for efficiency losses $\eta^{discharge}$=0.98, the total opportunity cost of discharging the EV during that time period would be $P_{5,1012,60}^{discharge} = (0.9kWh/(0.98)) * ((0.1\frac{\$}{kWh} + 0.08\frac{\$}{kWh}) - 0.018\frac{\$}{kWh}) = \$0.149$. In order for the discharging of this EV to be economical, the fleet would need to ask a price of at least \$0.149.

3.4.1.3 Place Ask and Bid ❸.

The third step is to combine the quantities and prices as asks and bids respectively and submit them to the market. To do this the agent chooses the EVs i with the lowest cost for charging $C_{i,l,t}^{charge}$ and discharging $C_{i,l,t}^{discharge}$ until the respective overall quantities

Q_t^{charge} and $Q_t^{discharge}$ are reached. Each quantity is submitted to the energy market at the average price from Equations 3.4 and 3.7, weighted by the amounts bought or sold. We only submit one ask and one bid for each time interval due to the minimum lot size of 1MW. We do not consider submitting multiple asks and bids for the same auction, even though this would increase the profits, because substantially larger fleets would be required to meet the minimum lot size. To reach the 1MW threshold one would need to collaborate with an aggregator.

Example: Take, for example, the following situation where the cost of charging EVs ID#1 and ID#2 are $C_{1,1012,59}^{charge} = 0.036\$$ and $C_{2,1012,59}^{charge} = 0.09\$$, and the corresponding bidding prices are $P_{1,1012,59} = 0.04\$$ and $P_{2,1012,59} = -0.02\$$ (t=59 means 4.45-5.00 pm). The negative price for EV ID#2 means in the time interval t=59 the market needs to pay Car2Go for the charging to be economically worthwhile. The state of charge of the batteries of the EVs are $SoC_1 = 0.3$ and $SoC_2 = 0.4$ respectively. FleetPower has determined the optimal quantity that should be offered to the market to be $Q_t^{charge} = 1.5kWh$. We also assume a battery capacity of $\Omega = 16.5kWh$, and a charging speed (γ) of 3.6kWh per hour (or 0.9kWh in 15 minutes) per EV. In this case FleetPower offers to provide $1.5kWh$ at a price of $0.016\frac{\$}{kWh}$, as $0.9kWh$ (depending on the amount that can be discharged with the infrastructure in the time constraint $0.9kWh$ and what SoC the battery is in, $0.6 * 16.5kWh$) can be provided from EV with ID#1, which has the lowest cost, and the remaining 0.6kWh will be provided from EV ID#2.

3.4.2 Endogeneity from Market Participation.

By participating in the market we may have an influence on market equilibrium, and this might in turn lead other market participants to behave differently. However, we argue that there is no endogeneity problem from reactions to our market participation as the asks and bids of other participants are aligned with their preferences. Discriminatory-price multi-unit auctions are not incentive-compatible but our approach will work with any mechanism. For example, the uniform-price multi-unit auction can be designed to be posterior regret-free (i.e., even though the mechanism is not incentive-compatible a priori, no one could benefit from not bidding their true valuation when evaluating allocation ex-post) (Bapna et al., 2005). Under these mechanisms other market participants have no incentive to alter their behavior in response to new market entrants. Our methodology will also work well with this kind of mechanism. While the revenues may be different, the structural results will not change.

3.5 Evidence from a Real-world Setting

For the evaluation we consider the 14 month period from May 1, 2014 to June 29, 2015. We train our model from the first two months from May 1, 2014 till June 29, 2014 and test it on the first week of auctions (the bids and asks for all the 15-minute intervals in a week are always submitted for the full week in advance, Monday to Sunday). Consequently we use a rolling time window for the training period of two months for each week of bidding. We test the algorithm for each week in the period from June 30, 2014 to June 29, 2015. From these training sets values for the rental likelihood model, expected driven kilometers, rental time, and rental profits are used to train the model. Based on this training period we evaluate the trained model over all one-week bidding blocks in that time period. There is no need to simulate the distribution of trips as we have an immense number of real driving transactions with which we can test our results, and a calibration of the driving data is therefore not necessary (as it is real data). The test period is given externally by the market while the training period is a constraint from the data collection perspective (we are limited to 14 month of collected data).

3.5.1 Energy Market Data: California ISO, Transnet BW, and Tennet

As illustrated in the Section 3.2.1, EV storage is particularly suited to real-time market operation due to the fast response times required (dispatch occurs within seconds of order acceptance). We therefore use auction data from these markets to determine the prices for balancing (charging as well as discharging) at each point in time. We use the data from the energy market operators in Stuttgart, Amsterdam, and San Diego. In Stuttgart, we use data from regelleistung.net, the German energy market operator, in Amsterdam we use data from Tennet, and in San Diego the data comes from California ISO. The data for Stuttgart contains the individual bids and asks with the respective quantities and prices for each 15-minute time interval. From these bids and asks we form the demand and supply curves. The clearing point Q^* sets the equilibrium, which determines whether the energy market operator settles the asks and bids placed by FleetPower (if the price P from the model is below the market price). For San Diego and Amsterdam we only know the clearing prices, though this still allows us to infer which bids and asks are accepted (the ones below the market price). The violin plot in Figure 3.10 shows the average regulation prices and their standard deviations for all three cities. As can be seen in all three, the prices for regulation reserves are quite variable (standard deviation ranging from 18.2 to 94.3). The low renewable energy content in the Dutch energy mix is responsible for significantly lower discharging prices (41.6 compared to 68.2) and standard deviations than in Stuttgart. This reduces the revenues for VPPs in the Netherlands. In contrast, the high renewable energy content in the energy mix in Germany and California leads to generally higher prices for discharging in Stuttgart and to large fluctuations in price in San Diego. This increases the revenues for VPPs in those countries, because those in Stuttgart can charge cheaply and sell large volumes of energy at higher prices, or in in San Diego they can sell smaller amounts of energy at extremely high prices at the high variation in the evening hours.

3.6 Analysis and Discussion

In this section we will discuss the evaluation of the business model in terms of the profits to the carsharing fleets and the implications for the grid. We will also describe the sensitivity analysis that we have conducted to show the robustness of our model.

3.6.1 Accuracy of the Model and Economic Sustainability

The proposed model creates a new business model for carsharing fleets, which is a natural extension to the traditional carsharing business. We are interested in whether this VPP business can increase the profits of carsharing fleets. Specifically we are interested how VPPs influence the gross (variable) profits, excluding overhead cost, because they are incurred regardless of the VPP model. Figure 3.11 shows the gross profits of Car2Go in Stuttgart, Amsterdam, and San Diego, both for carsharing only and for carsharing combined with a VPP. While the gross profits (black line) are volatile throughout the year, there is a clear seasonal pattern in the winter period in Amsterdam and Stuttgart. The additional benefits from using the fleet as a VPP (grey line) consistently increases profits during the entire year but is more pronounced in Stuttgart and San Diego. If we would break down the annual gross profits per EV at the example of Stuttgart, fleet owners make $3,900 from the rentals of an average EV, save $163 by charging at cheaper time intervals, and make an additional $14 from discharging electricity to the grid.

Our model and algorithms make decisions to maximize gross profits without knowing which rental transactions are going to happen in the future. Due to this uncertainty, the algorithm necessarily makes errors in its bidding process. Errors in committing EVs to a VPP when they could be rented out are the most significant

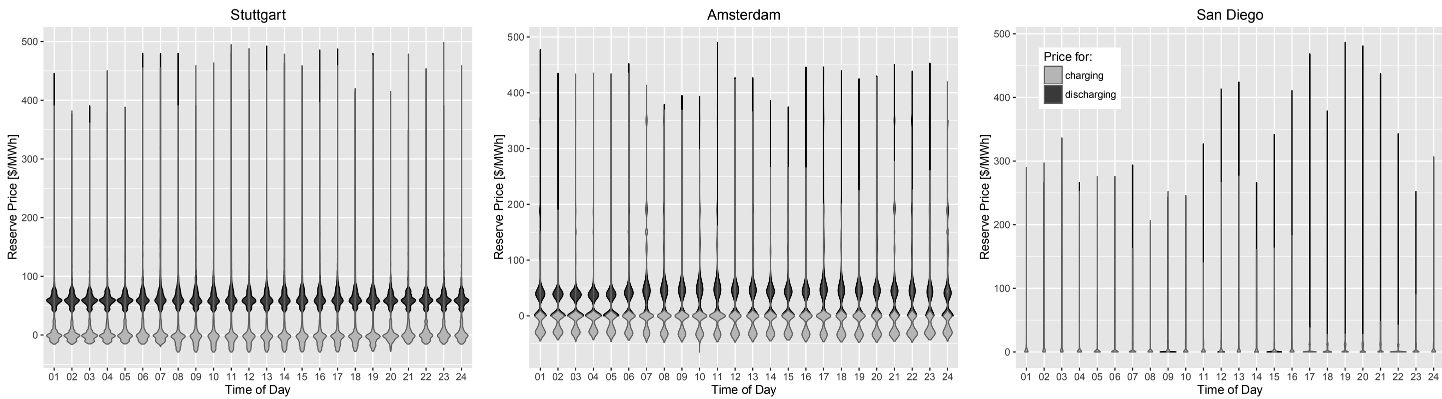

Figure 3.10: Regulation prices (June 30, 2014 to June 29, 2015), with standard deviation illustrating the extreme price volatility. Prices range from -60$\frac{\$}{MWh}$, at which the fleet can charge, to +500$\frac{\$}{MWh}$, at which energy can be sold back to the grid.

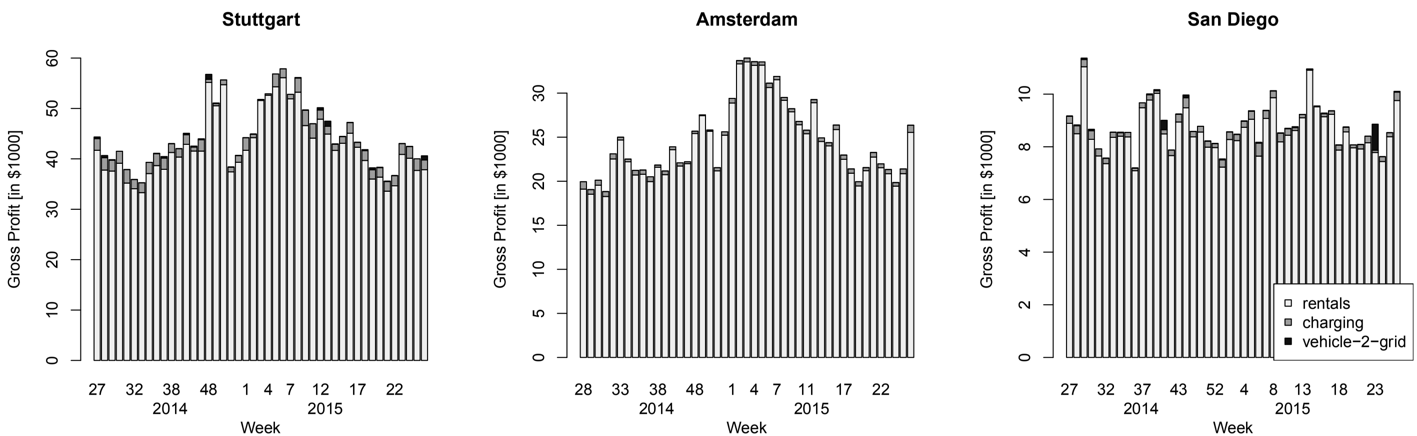

Figure 3.11: Shows the profits over the year. The profits from offering VPP power on the real-time market increases the gross profits of Car2Go consistently.

in terms of their impact on profitability due to the asymmetric pay-offs. The error matrix (Table 3.5) shows that the model performs extremely well in predicting when it would be more profitable to use EVs for rental transactions, rather than committing them to the VPP; in all three cities, errors on this occur less than 1% of the time. With the stratified sampling we are able to achieve this high accuracy for rental transactions as when the model is not very certain, it will make EVs available to be rented. However, this comes at the expense of not committing EVs to the VPP in periods when it would have been profitable. This happens between 42% and 80% of the time, depending on the misclassification weights per city. Table 3.6 shows that the decisions made have resulted in profits in absolute terms in all three cities. In particular, the earnings from EVs that act as VPPs exceed by a long way the opportunity cost of lost rentals. In Stuttgart, for example, Car2Go earned \$118,000 on top of its \$2m dollar rental business, while the rentals lost due to VPP commitments only caused losses of \$31,000. While 2,173 customer transactions could not be carried out immediately, the VPPs increased Car2Go's annual gross profits by 4.6% under the conditions observed in Stuttgart. Also in the other cities the use of FleetPower increased gross profits 1.7% in Amsterdam and 3% in San Diego. We attribute these differences as being due to the price levels in the case of Amsterdam (see Figure 3.10), and in San Diego as stemming from a lack of suitable infrastructure. We will analyze the effect of infrastructure in more detail in the next section. In all three cities the discharging capacity offered to the market was very seldom taken up by buyers (only 61 MWh was actually purchased for use), and in Amsterdam none of these asks were ever accepted. This was due to our high ask prices, which included the costs of battery depreciation. Currently 93% of the gross profits are earned by savings on the electricity bill for the EVs; in many cases the grid needs to urgently get rid of surplus electricity meaning that Car2Go actually gets paid to charge its EVs. For more information about the decision outcomes, see Table 3.7.

3.6.2 Impact on the Grid

Creating a VPP using an EV fleet provides a sound business case for a carsharing fleet. However, it is also beneficial to the grid and thereby society, because it provides additional reserve power to help keep the grid in balance at all times. This is already beneficial for the operation of the grid, but it becomes essential when a large proportion of weather-dependent renewable energy sources come on to the market. The VPP supports the grid by providing and consuming electricity on demand within seconds. The capacity that Car2Go provided to the market in each city is displayed in Figure

Table 3.5: Confusion (error) matrix (%): The matrix shows the accuracy of FleetPower's decisions. Because of the asymmetric pay-off the algorithm is trained not to bid for a VPP when rental transactions occur.

	Predicted					
Actual	**VPP**	**Rented**	**VPP**	**Rented**	**VPP**	**Rented**
VPP	53.00%	42.28%	28.11 %	68.12%	16.89%	80.27%
Rented	0.07%	4.64%	0.00%	3.76%	0.01%	2.83%
	[Stuttgart]		[Amsterdam]		[San Diego]	

Table 3.6: Confusion (error) matrix (in 1000 $): The matrix shows the monetary impact of FleetPower's decisions. The added value from VPP exceeds by far the losses from lost rentals in all cities.

	Predicted					
Actual	**VPP**	**Rented**	**VPP**	**Rented**	**VPP**	**Rented**
VPP	118	-	21	-	13	-
Rented	-31	1915	-1.4	1092	-0.7	396
	[Stuttgart]		[Amsterdam]		[San Diego]	

Table 3.7: Decision outcome results over a one-year period.

Description	**Stuttgart**	**Amsterdam**	**San Diego**
Discharged (V2G)			
Discharged energy sold (MWh)	54	0	7
Number of lost rentals	106	0	9
Increase in Gross profit (%)	0.4	0	0.6
Increase in Gross profit (in 1000 $)	7	0	2
Charged			
Quantity of energy bought (MWh)	1248	493	136
Number of lost rentals	2067	94	50
Increase in Gross profit (%)	4.2	1.7	2.4
Increase in Gross profit (in 1000 $)	80	19	9.5

3.12. While Car2Go consumes a substantial amount of surplus energy (a negative value on the y-axis means the total quantity charged), it discharges its EVs only infrequently in Stuttgart and San Diego and never in Amsterdam. Due to the low discharging prices, the cost of battery wear cannot be covered, with the consequence that asks to discharge EVs are accepted infrequently. We will elaborate on the impact of larger fleets on the balancing market in Section 3.6.6.

3.6.3 Sensitivity Analysis: Nonrecurring Events

In weeks when there is a high volume of rental transactions the fleet earns less from VPP operation, and conversely it earns more from VPP when the rental business is not going well. This can be inferred from the downward sloping trend in all three cities in Figure 3.13. When there are fewer rental transactions the probability of EVs being available for VPPs is higher and the chance of forgoing rental revenues is lower. In consequence the FleetPower business model is a natural complement to the existing carsharing business model; it allows fleets to bridge periods when rentals are declining with VPP profits of up to 8%, 4%, and 13% in Stuttgart, Amsterdam, and San Diego respectively (see Figure 3.13). When analyzing the data we found several outliers when events occur that cannot be inferred from the training period. For example, there were European, regional, and council elections held in Stuttgart on Sunday, May 25, 2014. Polling stations were open from 8 am to 6 pm, and this led more people than usual to rent a car that Sunday morning between 8 am and 11 am to drive to the polling stations. Our algorithm was not aware of the elections and made commitments to the energy market as if for a normal Sunday. The result was that on that particular day the number of people who would have rented a car was exceptionally high, but we had to turn 37 people away, with an opportunity cost of \$513. A natural extension of our algorithm would be to incorporate known events and holidays in order to anticipate such events and increase the accuracy and profitability of our model. This concept of adjustable autonomy is covered in previous literature (Bichler et al., 2010); we therefore did not include it in our algorithm, which makes the profit estimations of our algorithms more conservative.

3.6.4 Sensitivity Analysis: Charging Infrastructure

Charging infrastructure plays an important role for the business model, as more charging stations suggest there will be a higher average state of charge, leaving more room for both the rental and VPP business. Because the charging infrastructure is

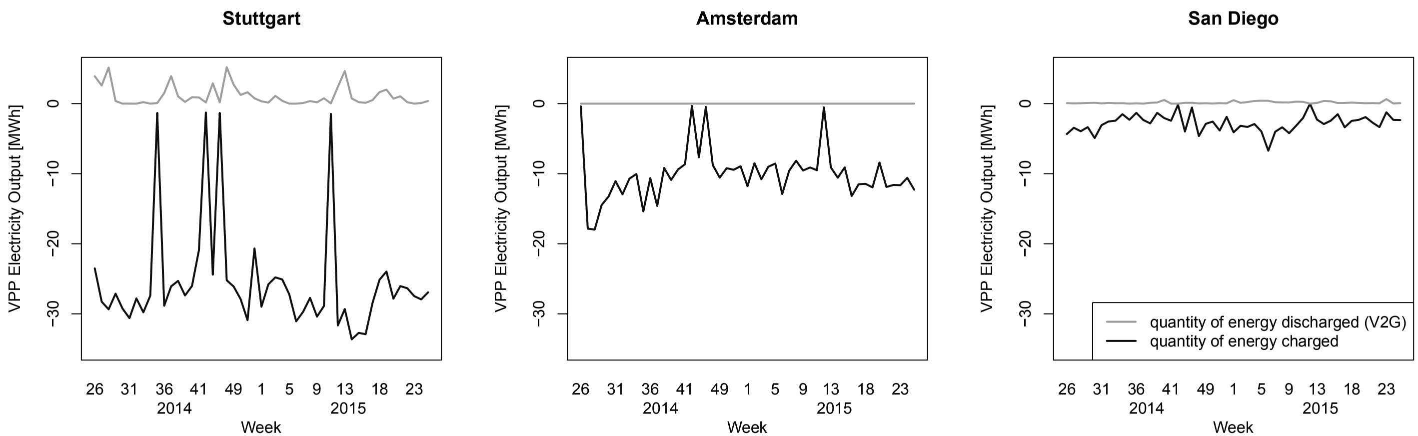

Figure 3.12: Shows the VPP output over the year. It is striking that vehicle-2-grid does not occur at all in Amsterdam, due to the low prices paid for discharging.

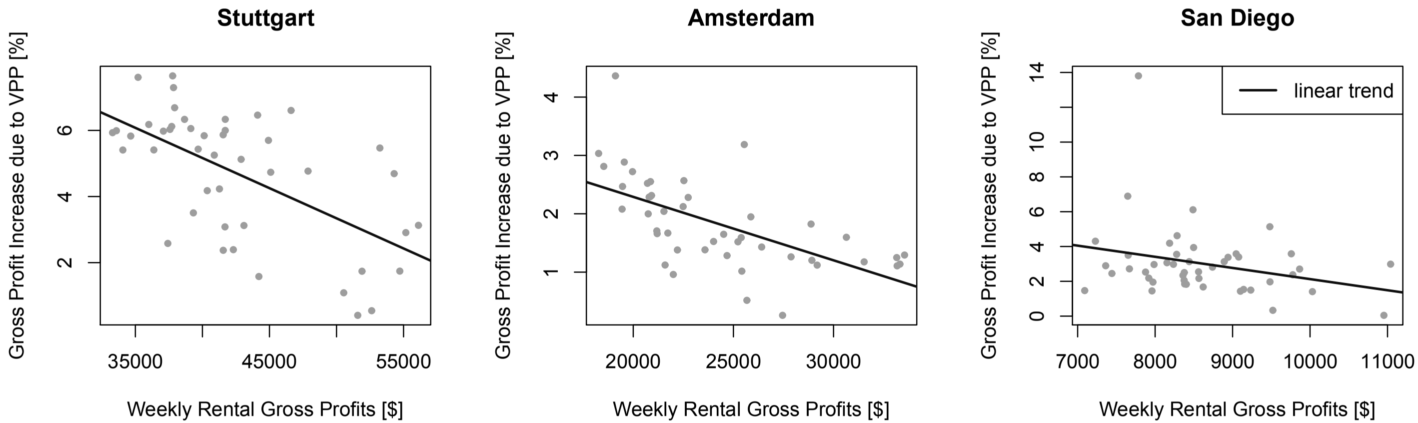

Figure 3.13: Shows the VPP profits as a function of the exogenous variable weekly rental profits. The downward sloping trend indicates that the profits from the VPPs complement periods where there are few rental transactions.

Table 3.8: Sensitivity analysis for charging station roll-out. Shows how the gross profit of Car2Go's virtual power plant business model increases as a function of charging stations with the growth factors 1 (as is), 1.5 (50% increase) and 2 (100% increase).

	Growth factor: 1	**Growth factor: 1.5**	**Growth factor: 2**
Stuttgart	↑ 4.6% gross profit	↑ 7.7% gross profit	↑ 8.7% gross profit
Amsterdam	↑ 1.7% gross profit	↑ 3.2% gross profit	↑ 3.8% gross profit
San Diego	↑ 3.0% gross profit	↑ 5.3% gross profit	↑ 5.5% gross profit

still under development we artificially increase the number of charging stations by 50% (factor of 1.5) and 100% (factor of 2) to assess the impact of future developments on the VPP business model. To do this we add charging stations to the parking spots that are most popular in terms of the number of hours parked. We stop placing charging stations when the total number of hours that EVs are parked at a charging station is twice what it is now. Surprisingly, of the 100 most popular parking spots in each city, 91 in Stuttgart already had charging stations, whereas only 57 did in Amsterdam, and 38 in San Diego. This result is especially surprising with regard to Amsterdam, which has almost seven times as many charging stations as Stuttgart. This means that both Amsterdam and San Diego could significantly improve the quality of their infrastructure by putting in charging stations in a few key locations. Charging stations in the Danil Goedkoopstraat 14 in Amsterdam, the 342-398 Market Street in San Diego, and the Eichenwaldallee 202 in Stuttgart would yield the largest improvements in infrastructure for these cities. A 59% increase in the number of hours that EVs are parked at charging stations (achieved through strategic placement of additional stations) has a linearly positive effect on the gross profits of Car2Go. If this were done, the gross profits would be increased by 8%, 3%, and 5% for Stuttgart, Amsterdam, and San Diego respectively. If the number of charging stations was increased by 100%, the profits for each city would increase by 9%, 4%, and 6% respectively (see Table 3.8). These results indicate that the charging stations in Stuttgart are already in particularly good locations, so that additional charging stations do not enhance profits as much. However, increasing the number of charging stations would significantly enhance profits in San Diego especially, but also in Amsterdam.

3.6.5 Sensitivity Analysis: Price Changes

As more renewable energy sources are brought into the energy mix in each of our three locations, more control reserve power (increase in $Q*$) will be needed to cover periods when these sources are either over- or underproducing. This increases the probability that higher priced bids from control reserves are also accepted - from discharging (V2G), for example. Therefore, we will analyse a scenario in which the need for secondary control reserves increases from the current demand Q^* to the future demand including more renewable energy sources $Q^{*'}$ (for both up- and down-regulation). We will model the future price change as illustrated for discharging on July 1 from midnight to 00:15 am in Figure 3.14. The increased demand causes the maximum acceptable price to rise from the current price P to the future price $P^{'}$. We can assess the difference in price discharge EVs between now and the future (ΔP) from the supply curves. The same happens to the demand for dumping surplus capacity; an increase in Q^* also changes the price to charge EVs. The price changes for both discharging and charging has a direct effect on the profitability of a VPP.

In Stuttgart we know the functions of the supply and demand curves, though this information was not available for San Diego and Amsterdam. We have therefore analyzed what effect changes in price have on profitability for Stuttgart. We consider a scenario in which the control reserve requirement Q^* doubles to $Q^{*'}$, and the impact of this is that the gross profits increase from 4.6% to 14.2%. This increase also has a positive effect on V2G usage; about two-thirds of the profits from VPPs are earned from V2G. The price increase makes discharging from EVs more cost-effective for fleets, as it means they are then reimbursed for the cost of battery depreciation.

3.6.6 Sensitivity Analysis: Scalability

The impact of a EV fleet of 350-500 cars on a country's real-time power reserve needs is negligible. However, a growth in the adoption of EVs raises the question of how this will impact the grid. Specifically we have analyzed what effect the number of EVs might have in terms of their ability to provide sufficient real-time power reserves. For that reason we have modeled the frequency distributions of the capacity provided by the fleet during the four different seasons and time blocks of the day: {night time (midnight to 7 am), morning (7 am to 10 am), noon (11 am to 2 pm), afternoon (3 pm to 6 pm), and evening (7 pm to midnight)}. In all 20 time-block/season combinations, it is frequently the case that the fleet did not provide any reserve capacity at all. To model that, we first proportionally sampled whether a fleet provided no control reserve capacity at all. If it provided a capacity greater than 0, we modeled distributions for each time-block/season combination (all normally distributed with the Kolmogorow-Smirnow test at a 5% significance level) and then picked random samples from this distribution to determine the reserve power that could potentially be provided by a

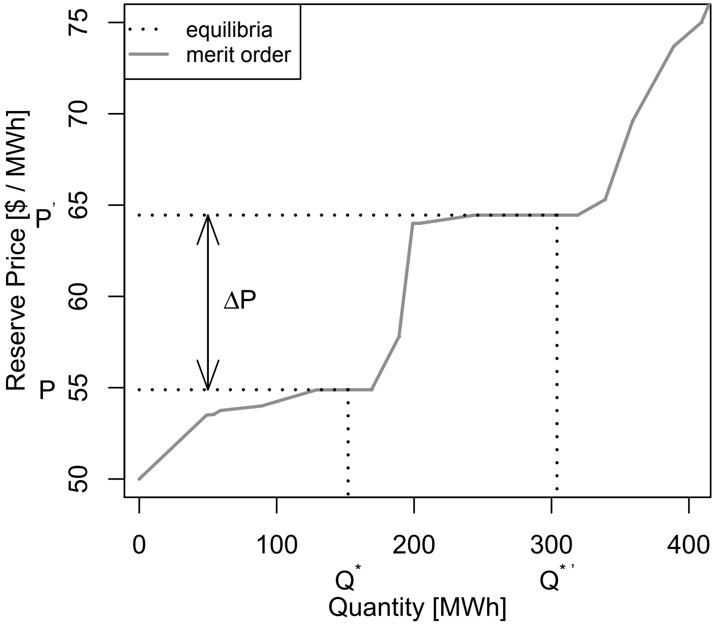

Figure 3.14: An increase in the reserve power requirement (from Q^* to $Q^{*'}$) shifts prices along the merit order (supply curve) to higher prices (from P to $P^{'}$) with a price difference of ΔP.

larger fleet or more fleets. However, for discharging in particular, large fleets currently also provide only a small share of the total power requirement of the real-time energy market. Even though the total storage capacity would be large enough, the priority given to renting out vehicles rather than charging and discharging at the current price levels would not allow the entire market to be balanced by EVs alone. However, if the demand for reserve power were to double, prices would reach a level that would justify using V2G on a large scale. We find that if half of Germany's cars were EVs, they would be able to deliver all the required reserve power needed to meet the demand during our test period from June 2014 to June 2015.

3.7 Conclusions

We have proposed and evaluated the FleetPower decision support system, which enables EV fleets to participate in the energy market as well as to continue their traditional rental business. We do this by using an intelligent agent that decides whether an EV at a specific location should be made available for rent, or whether it should be charged or discharged in form of a virtual power plant, providing an ancillary service. The system makes this decision based on forecasted rental transactions, charging, and discharging. Our tests show that using EVs for ancillary services consistently enhances gross profits for the EV fleet by 1.7% and 4.6%, depending on the location, representing an increase in annual gross profit of up to $86,000. This compares well to other studies, which found 14% in a stationary storage setting (Vytelingum et al., 2011), and up to 5% for electric vehicles (Schill, 2011). However, neither of these studies take into account that vehicles driving patterns are unknown a priori. In this study we have taken this probability of not serving rental customers into account with an asymmetric pay-off. We comparing the agent's performance across Stuttgart, Amsterdam, and San Diego, and are able to show how profitability is affected by the charging infrastructure in place and by energy prices on the regulation markets. V2G currently accounts for only a small proportion of these additional profits, as 90% of the profits come from electricity savings. However, we show that V2G has a strong impact on the gross profits of carsharing fleets when the demand for reserve power increases. Additionally, we demonstrate that the roll-out of additional charging stations in the future will have a positive effect on the business model, and we make recommendations on how GPS data on parking duration could be used to position these stations strategically. With this decision support system it is possible to replace carbon-intensive back-up capacity with clean energy storage, but as there are not yet enough EVs on the street, they need to be combined with other fast-response technologies such as biogas or hydropower in order to balance volatile renewable energy sources such as wind or solar.

Chapter 4

Electric Vehicle Virtual Power Plant Dilemma: Grid Balancing Versus Customer Mobility [1]

4.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) has stated that human-induced climate change causes eight systematic environmental hazards. Among these

[1] This paper is currently under peer review at a journal in the 3^{rd} round.
Parts of this chapter appear in the following conference proceedings:
Kahlen, M.T., Ketter, W. & Dalen, J. van (2014). Balancing with Electric Vehicles: A Profitable Business Model. *In Proceedings of the 22nd European Conference on Information Systems* (pp. 1-15). Tel Aviv, Israel. (9-11 June 2014).
Kahlen, M.T., Ketter, W. & Dalen, J. van (2014). Real-time Virtual Power Plant Decision Support. *Tenth Symposium on Statistical Challenges in eCommerce Research (SCECR 2014).* Tel Aviv, Israel (12-13 June 2014).
Kahlen, M.T. (2014). Agent-based Methods for Eliciting Customer Preferences to Guide Decision-making in Complex Energy Networks (Doctoral Consortium). *In Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014)* (pp. 1715-1716). Paris, France: International Foundation for Autonomous Agents and Multiagent Systems. (5-9 May 2014)
Kahlen, M.T., Ketter, W. & Dalen, J. van (2014). Agent-coordinated Virtual Power Plants of Electric Vehicles (Extended Abstract). *In Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014)* (pp. 1547-1548). Paris, France: International Foundation for Autonomous Agents and Multiagent Systems. (5-9 May 2014)

are flooding, extreme and variable precipitation, increasing frequency and intensity of extreme heat, drought, ocean acidification, and loss of the Arctic sea ice (Field, 2014). To mitigate these risks we need to reduce CO_2 emissions. The use of electric vehicles (EVs) in combination with renewable energy sources is an essential step in reducing emissions. However, renewable energy sources are extremely intermittent: they produce electricity according to the weather - not necessarily to what is needed. Differences between the production and consumption of energy destabilize the grid, leading to blackouts, which can have serious economic and physical consequences, as for example in hospitals, or traffic. In view of its perishable nature electricity cannot be stored in large amounts. As a consequence, balancing the demand and supply of electricity in the grid plays a central role in realizing the potential of volatile renewable energy sources for consumers of electricity. Currently, idle power plants serve as a back-up to ensure that electricity is available at all times. This approach is not only extremely inefficient and expensive for the society, but also limits the accommodation of increasing shares of renewable energy sources. The reason for this is that the grid has to operate increasingly under variable supply from renewable energy sources while the market share of dispatchable power plants such as coal or gas diminishes and therefore cannot guarantee back-up at all times. Our approach offers an alternative with VPPs.

As EVs become more widely adopted, storage capacity for electricity becomes available. It has been suggested that this capacity could be employed to offer balancing services to the grid (Sioshansi, 2012; Vytelingum et al., 2011). But there is a trade-off between the cost of operating this storage, such as battery wear, and the potential profits. For example the battery has to be replaced already after 7 rather than 10 years but profits increase by 4%. In this research, we consider the electricity stored in an EV battery as inventory. The battery can be allocated to four mutually exclusive states. It can either charge (add inventory), discharge for renting (decrease inventory), discharge to the grid (decrease inventory), or be idle (no change in inventory). While the optimal allocation of the EV over time is a simple multi-period inventory flow problem, the allocation is much more complicated under uncertain energy prices when it is not known in advance when and where EVs will be used like for example in a carsharing fleet. In the basic flow where a private person owns one EV, inventory is substitutable. The owner can decide between charging, discharging, driving, and being idle, which is a well-studied subject (Valogianni et al., 2014a; Fridgen et al., 2014). When considering fleets of EVs, location matters, as product demand (energy for rentals) depends on location. We make a trade-off between a class of demand where location matters (drivers want a car to be close to their departure location) for a class of demand where location does not matter (vehicles can discharge to the grid from any capable charging point).

We develop a model to analyze the profit maximizing strategy for a fleet of EVs (in particular car-sharing fleets) across the districts of cities. VPPs are a collection of distributed energy sources, in our case, EVs, that are centrally managed to generate power at consumption peaks and absorb excess electricity when consumption is low (Ausubel and Cramton, 2010). When EVs are charged or discharged to the grid, they are aggregated to virtual power plants (VPP) which act on fluctuating electricity price signals. Our strategy optimizes electricity purchases of EV fleet owners on the market to charge the fleet for the purposes of facilitating driving, or of discharging at a later stage for a price premium. Our model is validated with data from real electric vehicles, whose movement we track with GSM (Global System for Mobile Communications) and GPS (Global Positioning System). This technology provides us real-time information on battery and location of the EVs.

Previous research has addressed the impact of EVs on the technical efficiency of the smart grid, while assuming that driving patterns are exogenously given (Sioshansi, 2012) or battery storage is static (Vytelingum et al., 2011). When driving patterns are regarded as a given, this dispenses with any uncertainty over when EVs will be available to store electricity. In a simulation we show that our model works in an uncertain environment where trips are not known in advance and we take the corresponding costs of immobility of customers for the fleet owner into account. Fleet owners usually have the option to participate in several electricity markets to benefit from the highest price difference within and between these markets. As we have studied the regulation market in Chapter 3, we now focus on the day-ahead market. Note, however, that this makes our profit estimates more conservative, as the price difference across markets is higher than within only one market. From the day-ahead market we extract the hourly bid and ask data from real-world electricity auctions to make inferences about the current and future behavior of market participants using large-scale data analytics. We have built a detailed replica model of the electricity market, which models the electricity market at the bid and ask level resolution. We can compute the actual market clearing prices as they occurred in 2015 for each respective hour without the EVs. However, the advantage of our simulation is that we can add additional bids and asks into this market to see how the market price would change if EVs were place bids and asks as well and if competition increases. If there is increased charging demand from the EVs the demand curve shifts, if the vehicles discharge the supply curve shifts. This is done according to the market clearing mechanism. Based on this, we estimate the impact of various penetration levels of EVs on the demand and supply in the energy market, the electricity prices that consumers pay, and CO_2 emissions. To study these effects, we validate our model in a simulation calibrated with real-life data from the Nord Pool Spot ELSPOT electricity market in Northern Europe and a fleet of 1,100 EVs from Daimlers car-sharing fleet Car2Go in San Diego, Amsterdam, and Stuttgart and 400 EVs from BMW's carsharing fleet DriveNow in Copenhagen. These carsharing EVs are rented out in free float, meaning that any customer can pick up a car within the city boundaries, as long as he returns it anywhere within the city boundaries. An incentive scheme of 10 free driving minutes encourages parking at charging stations to recharge the EVs when the state of charge is below 20%. In our simulation, only vehicles that are parked at one of the charging stations can interact with the electricity market. Rentals occur on the spot as cars cannot be reserved more than 30 minutes in advance.

Our model addresses the challenges of the current and future energy landscape in terms of the triple bottom line: the impact for people, planet, and profit (Nations, 1992). Our contribution is to help embedding sustainable renewable energy sources in energy systems and add to the existing knowledge base regarding EV storage and multi-period inventory flow models with location dependent demand. We find that our recommended strategy lowers energy prices for consumers (people) by 3.4%, mitigates CO_2 emissions (planet) by 3%, and offers profit increases of 4.3% for fleet owners (profit).

The paper is structured as follows. First, we review related literature and the theoretical background of energy markets (Section 4.2), and then proceed to describe the trading model for EV fleet owners (Section 4.3). Next, we go in detail about the methods we apply, how we analyze the model, and how we deal with uncertainty (Section 4.4). Afterwards, we explain how we calibrate and evaluate our model with real-world data (Section 4.5). The analysis and the impact of our strategy on people, planet, and profit are described in Section 4.6. We present a summary and conclusion of our research combined with an outlook on future work in Section 4.7.

4.2 Theoretical Background

This section describes and explains relevant research and the general setting of balancing renewable energy sources with EV fleets. First, we will describe the research that has been done on charging EV fleets with variable prices to save cost. Consequently, we will position our research within the literature on EVs and the vehicle-2-grid context of selling electricity back to the grid. Next, the methodological background from related topics will be given and auction markets, which are the basis for variable electricity pricing are discussed. Finally, the electricity market functioning will be described and how fleet owners can participate in this market.

4.2.1 Smart Charging of Electric Vehicles

The average additional demand for EV charging is no significant problem to the generation capacity in the long term (Sioshansi, 2012), because capacity can be increased gradually in the system. However, large numbers of EVs can cause problems for grid operations: decentral transformers and regional substations can quickly become overloaded when not adequately managed (Sioshansi, 2012). Mak et al. (2013) outline how battery infrastructure should be planned along highways and how it drives adoption of EVs. Avci et al. (2015) explain the effect of battery swapping stations on the take-up of EVs and their environmental impact. Both studies emphasize the need for research on the implication from charging on the grid. Some research suggests that smart charging should incorporate price incentives that help address the peak-load issues for transformers and substations (Valogianni et al., 2014b; Wolfson et al., 2011a). Other studies recommend users to share information about when they drive their EVs (Fridgen et al., 2014) or indicate that area pricing (Flath et al., 2013) be used to reduce the impact of EVs on the grid. However, no study has focused on the management of large-scale storage using EV fleets distributed over different city districts with real market and electric vehicle data.

4.2.2 Vehicle-2-Grid: Electric Vehicle Batteries to Stock Electricity

Fleet owners with large numbers of EVs influence the demand for electricity by charging their EVs (Gottwalt et al., 2011), but they can also influence the supply by making additional energy available to the grid, especially during demand peaks. This has been referred to as vehicle-to-grid (V2G). Current charging infrastructure standards, Type 1 chargers (SAE J1772, standard in North America and Japan), and Type 2 chargers (IEC 62196, standard in the European Union) chargers, support V2G technology. These standards have been successfully applied for V2G in practice. For example, the Los Angeles Air Force Base applies V2G to create a grid independent military base microgrid (Marnay et al., 2013). The University of Delaware applies V2G for energy trading (Shinzaki et al., 2015), and in the Edison Project in Switzerland and Denmark it is applied for demonstration purposes (`www.edison-net.dk`). Moghaddas-Tafreshi (2011) or He et al. (2016) develop bidding strategies for stationary storage to participate in electricity markets.

Moghaddas-Tafreshi (2011) built a model to bid in both energy and operating reserve markets with great success. Building on this, He et al. (2016) developed and extension of a bidding model, which includes battery life cycles as a critical cost factor as well. In this work we also consider battery life cycles, but additionally look at the unavailability of vehicles due to rentals and the implications for competition on electricity markets, which adds an additional layer of complexity. Vytelingum et al. (2011) investigated the effects of using a static storage for a household to store energy when it is cheap and showed a 14% saving in the energy bill, with carbon emissions also being reduced by 7%. Other studies have found the yearly benefits of V2G to be in the range of \$20-120 (Peterson et al., 2010) and \$135-151 (Reichert, 2010), acknowledging that battery cost are a crucial factor in the profitability. With a price sensitivity analysis, Reichert (2010) show that batteries are seldom used for V2G when battery degradation costs \$50 per MWh, whereas they can be profitably used at a degradation cost of \$10 per MWh. The use of EVs as VPPs therefore depends on advances in battery technology. Additionally, Tomic and Kempton (2007) show that V2G profitability is subject to the market setup; the shorter the interval between the sale of electricity and the physical delivery, the larger the benefits. Kahlen and Ketter (2015) extend this finding by showing that charging costs can be decreased by more than 7% when trading on ancillary service markets, and that V2G activities therefore can become profitable for fleet owners.

Relatively little research has been conducted into the impact of uncertainty of rental demand and not knowing in advance when EVs are needed for driving at which location. In contrast to previous work, our paper works also when rental demand is not known in advance.

4.2.3 Methodological Background and Parallels to the Caching Literature

Businesses are continuously under pressure to make their operations sustainable through green operations or closed-loop supply chains (for example, Kleindorfer et al. (2005)). Likewise, the automobile industry needs to innovate. Carsharing is an innovation that increases vehicle utilization. We show how electric vehicle fleet owners can utilize the EVs to their full potential by additionally using their storage.

This potential can be achieved by allocating the storage efficiently between the four different states (charging, discharging, renting, idle). We consider it as a multi-period inventory flow problem as the fleet owner needs to decide by how much he should charge, discharge, and keep vehicles idle to rent for rental customers to maximize his profits. To make this decision we build a model that is informed by previous research in the caching literature, which has addressed a similar storage problem. Caching means to store data in advance to improve web browsing performance so that frequently accessed information is locally stored and does not need to be downloaded when needed. Mookerjee and Tan (2002) analytically analyze the last recently used policy, which caches the most frequently accessed documents. An extension to this policy studies the price differentiation between different caching protocols (Hosanagar et al., 2005). Storing information on anticipated demand is similar to our EV storage problem, which is why we follow a similar modeling approach of estimating demand, developing a model, and consequently empirically testing the model. A parallel to the fleet dimension of our research can be drawn to collaborative caching, in which items are cached in multiple locations (for example other computers within an organization) (Datta et al., 2003). This is relevant to our paper, as there is storage which is shared among several users (similar to car-sharing), yet location is critical because if one's item is stored in someone else's cache, accessing the item will be slower (like an EV parked further away). For our problem location is important, which was modelled with an inhomogeneous Poisson process in Hosanagar and Tan (2012), but in addition to that time is a crucial factor for our model, as the demand for vehicles differs over the day for example during rush hours. Hosanagar and Tan (2012) also find that it is difficult to manage this shared cache centrally because some users of the centrally managed cache system benefit more than others from the optimal policy. To address fairness considerations we use auction markets to allocate the EVs to their four respective states according to the states valuations. This process of market optimization has previously been described in management science as a smart market (McCabe et al., 1991; Gallien and Wein, 2005; Bichler et al., 2010). McCabe et al. (1991) and Bichler et al. (2010) have highlighted the relevance of smart markets for the electric power system. Energy providers are faced with a resource allocation problem. Increasingly volatile energy supply and fluctuating energy demand make it difficult to predict when to deploy energy storage and additional generators. By auctioning off the storage of EVs we are able to signal the maximum willingness to buy or sell energy to the market so that the EVs will always be allocated profitably. The next section describes the market mechanism of this auction.

4.2.4 Day-ahead Electricity Wholesale Market Mechanism

While fleet owners normally charge their EVs with a flat electricity tariff negotiated with an electricity provider, they have to enter the wholesale market if they want to benefit from price differences over time (arbitrage). They need to determine the quantity of electricity that they are willing to store or sell back to the grid for each hour interval of the next day and the minimum price they would like to sell for and the maximum price they would be willing to buy this quantity for. This quantity and price can be matched with other willing buyers and sellers in the day-ahead electricity wholesale market. In this section we will explain the functioning of this market before we go in detail on how our model makes use of this market. We consider a day-ahead market for electricity, which is common in western economies. The market is a platform for sellers and buyers of electricity to make contracts, or 'orders', for the delivery of electricity the following day. Agreed prices vary for every hour of the next day. Energy prices are determined to clear the market by means of a double auction analogous to (reverse) multi-unit auctions, in which multiple buyers and sellers participate (Krishna, 2002).

In the energy market, suppliers j submit 'asks', that state the quantity $Q^j_{S,t}$ they would like to sell and the lowest price P^j_S they are willing to accept, for the time interval t. The buyers k place 'bids' that state the quantity Q^k_D they want to buy and indicate the maximum price P^k_D they are willing to pay for the specified time interval. The fleet owners assume the role of suppliers when they discharge the EVs, and the role of buyers when they charge EVs. Once all bids and asks are placed, they are arranged by the market operator in a merit order: the cheapest asks and the bids with the greatest willingness to pay are prioritized, as illustrated in Figure 4.1. The asks in the merit order make up the supply curve for electricity, while the bids form the demand curve for electricity. The intersection of both functions defines the equilibrium clearing price P^*_t that equalizes supply and demand. In Figure 4.1 the clearing price P^*_1 is equal to \$41.5, which is the same for all executed bids (1, 4, and 8) and asks (3, 2, and partially 7). The total clearing quantity Q^*_t is the sum of executed order quantities equal to 20MWh. All (partial) orders to the right of the clearing point are either asks that sell at a price that no consumers are ready to pay, or bids by consumers that no seller is willing to sell and are thus rejected.

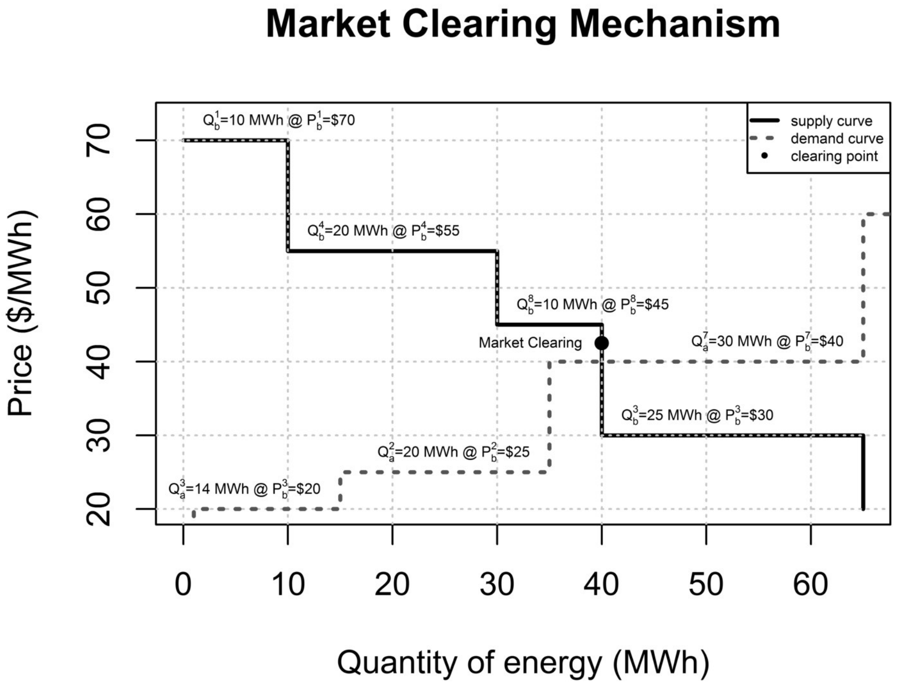

Figure 4.1: Illustration of the wholesale market clearing mechanism for time t.

4.3 Model Description

Our study takes the perspective of EV fleet owners operating VPPs by aggregating the capacity of their EVs, which we consider as inventory, that are not in use. The fleet owner allocates the EVs to states over time: to charging (adding inventory), discharging to the grid (decreasing inventory), or being idle (not changing inventory), which can lead to the state discharging for renting (decreasing inventory). The idea of our model is that the energy stored in the batteries of the EVs is used to meet peak demand in electricity consumption. Fleet owners that want to earn additional revenues from buying and selling electricity are concerned that these activities will jeopardize the much more profitable rental transactions. They will only engage in buying or selling electricity for arbitrage purposes when they can be sure that they will not have to turn away rental customers. For that they need to know how many vehicles are available and the demand for rentals in a given time interval. Vehicles that are not rented out can be used for charging and discharging as long as this does not interfere with rentals in the next time interval due to, for instance, a too low battery after discharging.

Rental patterns may differ throughout different parts of the city. As it is expensive to relocate vehicles, which requires staff and resources, the availability of vehicles for arbitrage differs between districts. Fleet owners can exploit this difference to use vehicles at less popular rental locations, which depends on the time of day, for arbitrage. We model these differences in demand across locations to be able to evaluate location dependent vehicle allocation decisions. We assume that demand within a city district (l) is relatively homogenous as people are willing to walk short distances. This assumption is supported by our analysis in Section 4.6, which shows that there are distinct differences in rental demand across the districts. The day-ahead electricity market closes at noon for the next day, meaning that the bids and asks with the respective quantities to charge and discharge need to be submitted between twelve and 36 hours in advance for all 24 hour time intervals. Carsharing fleets where customers decide spontaneously whether to rent a car or not (cars are reserved maximally 30 minutes in advance) cannot tell with certainty how many EVs will be available at a certain location and what the demand is for these cars twelve hours in advance. They do have, however, past data on the availability of EVs and the rental demand at these locations. Fleet owners can use this to determine the decision parameters price P_t and quantity Q_t for each hourly time interval of the next day.

4.3.1 Trading Strategy

In this model a fleet owner auctions off the idle storage capacity of EVs, which optimally allocates the EVs in the fleet to its respective state (charging, discharging, idle, or renting) by maximizing the profits for fleet owners. This strategy prescribes the fleet owners trading behavior and specifies general rules about when charging the fleet, selling energy back to the grid, or postponing to do either will be most beneficial.

A fleet owner maximizes profits by making a tradeoff between buying and selling electricity from the EVs to the grid on the one hand and making profits from rentals on the other hand. If the fleet owner buys or sells more electricity this will reduce the rental profits and vice versa. This profit maximization is a decision for the fleet owner to determine the price $P_{D,t}$ he is maximally willing to pay to buy the quantity of electricity $Q_{D,t}$ and to determine the minimum price $P_{S,t}$ he is willing to accept to sell the quantity of electricity $Q_{S,t}$ for each hourly time interval t. The remaining capacity is available for rental. When this decision on the fleet allocation is made a day-ahead, both the price for electricity P^* (the market clearing price) and the rental demand per location l are uncertain. The profits for a fleet owner are determined as:

$$arg\ max\ f(Q_{S,t}, P_{S,t}, Q_{D,t}, P_{D,t}) = \sum_{t=0}^{T} (Q_{S,t}^{EV} * P_t^*) - (Q_{D,t}^{EV} * (P_t^* - b)) + \sum_{l=1}^{L} m_{l,t} * \pi_m^m \tag{4.1}$$

where T is the planning horizon in number of time intervals t, b is the battery depreciation cost per kWh discharged, L is the number of city districts in the fleet owner's operating area, $m_{l,t}$ are the miles rented in district l at time interval t, and $\pi_m^{'}$ is the marginal profit per mile rented. Note that the decision variables $P_{S,t}$ and $P_{D,t}$ only have an indirect influence on profits through the market clearing price P^* (see Section 4.2.4).

The total amount of energy that can be discharged during a specific hour and made available to the grid, the ask quantity for discharging, is the sum of the energy from all districts L and can be expressed in terms of the electricity stored $q_{l,S,t}$ at location l. The amount of energy available for discharging (V2G) during a specific time interval is defined as:

$$Q_{S,t}^{EV} = \sum_{l=0}^{L} q_{l,S,t} * e_d \tag{4.2}$$

where $q_{l,S,t}$ is the electricity stored at location l as defined in Equation 4.9 in excess of the electricity needed for rentals, and e_D is the efficiency rate for discharging. Equation 4.2 takes into account the charging inefficiency e_D, including conversion losses, which occur when energy is converted from direct current to alternating current.

The total amount of energy that the batteries can be charged with Q_D^{EV} (which is at the same time the bid quantity for charging), is expressed by the storage available in each city district:

$$Q_{D,t}^{EV} = \sum_{l=1}^{L} q_{D,l,t} * e_c \tag{4.3}$$

where e_G is the efficiency rate for charging which captures the energy losses when converting from alternating current to direct current, and $q_{l,S,t}$ is the storage available at location l defined in Equation 4.10 in excess of the storage needed for rentals.

The following constraints need to be respected in order to meet the physical grid constraints and driving needs of the EVs:

The electricity storage levels of EVs are defined as:

$$S_{i,t+1} = S_{i,t} - q_{i,S,t} * e_d + q_{D,i,t} * e_c - r_{i,t} \tag{4.4}$$

where r is the amount of energy used for driving. Equation 4.4 accounts for storage capacity left over from previous hours, discharging and charging that occurred in the previous hour, and the energy used for driving during that hour.

Equation 4.5 defines the energy used for driving by the miles covered by a certain car in a specific hour multiplied by the fuel economy:

$$r_{i,t} = m_{i,t} * F_i \tag{4.5}$$

where F is the fuel efficiency.

A battery cannot be under- or overcharged, through Equation 4.4 it indirectly makes sure that a fleet owner does not bid or ask for more electricity than he can store:

$$S_{min_i} \leq S_{i,t} \leq S_{max_i} \tag{4.6}$$

where S_{min} is the minimum storage, and S_{max} is the maximum storage capacity of an EV.

Equation 4.7 expresses the fact that an EV can only be driven until the battery is empty:

Table 4.1: Table of notation.

Variable	**Description**
a	duration of a rental cycle pattern
b	battery depreciation costs per kWh of discharging
e_c	percentage of efficiency during charging and conversion
e_d	percentage of efficiency during discharging
F	fuel efficiency
i	a specific EV
I	number of EVs in the market
j	a specific ask of a supplier of electricity
k	a specific bid of a buyer of electricity
l	a district within a city (location)
L	number of unique districts in the city
m	miles driven
P^*	energy price (market clearing price)
P_D	price of a bid (demand)
P_R	price of a rental trip
P_S	price of an ask (supply)
q_D	storage available at location l in excess of the storage needed for rentals
q_S	electricity stored at location l in excess of the electricity needed for rentals
Q_D	potential to store quantities of electricity in the EVs; quantity of a bid (demand)
Q_S	quantity of electricity stored in the EVs; quantity of an ask (supply)
r	amount of energy used for rentals
S	state of charge of an EV at the beginning of an hour
S_{max}	maximum storage capacity of an EV
S_{min}	minimum storage capacity of an EV
t	specified hourly time interval for delivering energy
T	number of hours over which the problem is maximized
$\pi_m^{'}$	the marginal profit per mile rented
τ	numbers of hours of the training period

$$S_{i,t} \geq r_{i,t} \tag{4.7}$$

Equation 4.8 defines the ask quantities which should not exceed the required storage level for rentals in the next time interval to have enough storage to meet future rental demand:

$$\widehat{Q}^{EV}_{S,(t+1)} - \widehat{Q}^{EV}_{S,t} \leq \sum_{i=1}^{I} S_{i,(t+1)} \tag{4.8}$$

To summarize, the fleet owner submits offers to the market to charge and discharge for every time interval. These offers contain both a quantity and a reservation price, which depends on the state of charge of the EV storage, as well as on the battery costs. However, the market may or may not accept these offers depending on the composition of the offer prices from the fleet owner and other market participants. The market auction mechanism ultimately decides when EVs will charge and discharge.

4.4 Methodology

In this section we will describe how we will solve the EV allocation problem of the fleet owner with respect to the decision variables (quantities and prices to sell and buy electricity) and how we deal with the uncertainty in rental demand and electricity clearing prices.

Let us consider the allocation process of EVs we evaluate it, which is illustrated in Figure 4.2. First, fleet owners forecast the number of available EVs and their storage potential in each district of a given city. On the one hand, the forecast minimizes the cost of procuring energy for charging and sets the price at which energy should be sold for from the VPP. On the other hand, the forecast ensures that rental consumers can meet their mobility goals. The model fulfills these objectives by making decisions based on wholesale price differences across time and the forecasted availability of EVs per districts as an arbitrage in the same market over time. This requires only a slight reconfiguration of current EV fleet rental business models, as our model uses mostly idle EVs connected to a charging station. The benefits from trading can be achieved by extending the existing rental business model. We forecast the allocation during a training period and evaluate the additional profits during a test period (holdout set). If an ask to discharge or a bid to charge an EV is accepted, we add those profits and savings to the fleet owner's bottom line. But we also deduct opportunity cost from

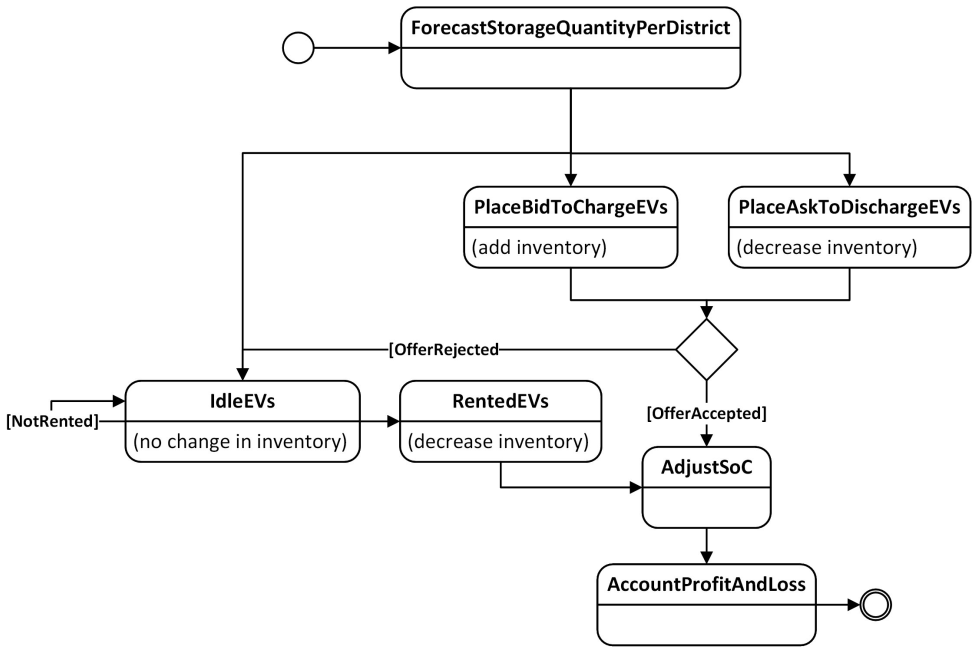

Figure 4.2: Diagram representing the states of the virtual power plant at a specific time interval t.

the bottom line if we observe that more EVs are rented in a period than predicted, for which we use the empirical distribution from rental transactions duration and location. These opportunity cost may arise because fleet owners have committed to selling the storage twelve to 36 hours in advance and as a result cannot rent EVs to customers in these cases.

4.4.1 Determining the Quantity to Charge (q_D) and to Discharge (q_S)

The demand for vehicles is uncertain at the point that the fleet owner has to submit his or her asks and bids. In order for a fleet owner to place any orders, he or she needs indicators about future rental demand for EVs per location, their availability, and their state of charge. This information is provided by the GSM and GPS of the EVs in real time. However, the information is needed between twelve and 36 hours in advance, when the orders are submitted to the day-ahead market the noon before. Knowing one day-ahead which EV will be used when and where is virtually impossible. Firstly, individuals cannot always state in advance when they need a car, and secondly, even if that were the case, this information may not be available to fleet owners. However, fleet owners can exploit the properties of VPPs to make aggregate EV usage predictions. We use the a bottom up model to forecast the aggregate energy need for driving in each district of a city for a given hour and then combine it into one bid or ask (Equation 4.2 and 4.3). Location is critical for the rentals, it is not important for the grid from where EVs deliver the actual physical electricity as a service to the grid - so long as the asks and bids that are accepted by the market are honored by some EV from the fleet. Hosanagar and Tan (2012) use an inhomogeneous Poisson process to model locality in the caching literature, but as we use both locality and time, we use the empirical distribution of the rental demand.

To determine the amount of electricity that can be charged (Q_D^k) and discharged (Q_S^j) we forecast the amount of idle storage to charge (q_D) and discharge (q_S) available at location l for timeslot t a day-ahead. First, we analyze the autocorrelation of the amount available in the districts (how the amount depends on itself at different points in time) to check for randomness. Figure 4.3, 4.4, and 4.5 show the autocorrelation plots for the total amount of storage available with a lag on the x axis and how the lag is correlated with the total amount of storage on the y axis. The figures show alternating sequences of positive and negative peaks. These peaks are not decaying below the 95% confidence band indicating a strong dynamic structure in the data. In particular these patterns have a sinusoidal signature, which we use to stationarize the data. The difference in patterns across districts leads us to conclude that there is a cyclical rental pattern that is different per location. While some districts, such as for example Down Town San Diego, exhibit daily recurring patterns (see Figure 4.3), other districts, such as Indre By Copenhagen exhibit weekly patterns (see Figure 4.4). Yet other districts have a combination of weekly and daily patterns such as for example Nieuw-West in Amsterdam (see Figure 4.5). To capture these cyclical repeating patterns a sinusoidal model is most appropriate for forecasting because data for the previous twelve to 36 hours is not available for moving average based models. The storage available for charging in excess of vehicles used for rentals at location l and time t is determined by:

$$\widehat{q}_{D,l,t} = \sin \frac{2\pi}{\alpha_l} * t_l + \cos \frac{2\pi}{\alpha_l} * t_l \tag{4.9}$$

where α is the duration in which the cyclical rental pattern repeats.

The storage available for discharging in excess of vehicles and electricity used for rentals at location l and time t is determined by:

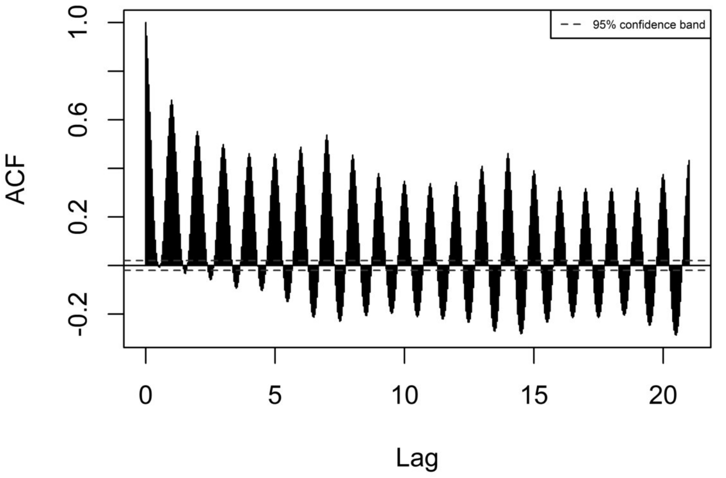

Figure 4.3: The autocorrelation of the storage availability in Down Town San Diego exhibits daily patterns.

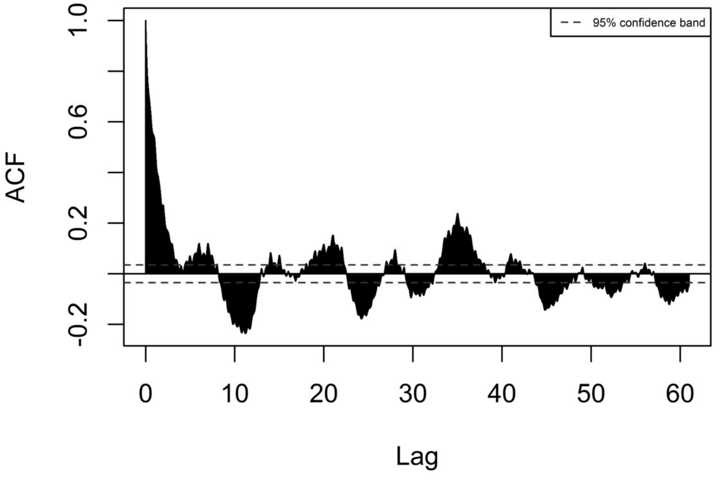

Figure 4.4: The autocorrelation of the storage availability in the Indre By district in Copenhagen exhibits weekly patterns.

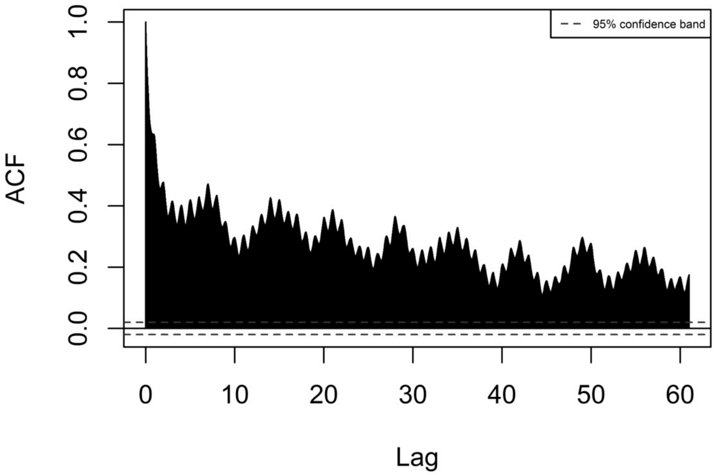

Figure 4.5: The autocorrelation of storage availability in the Nieuw-West district in Amsterdam shows both daily and weekly patterns.

$$\widehat{q}_{l,S,t} = \sin \frac{2\pi}{\alpha_l} * t_l + \cos \frac{2\pi}{\alpha_l} * t_l \tag{4.10}$$

We develop a mean asymmetric weighted (MAW) objective function that weights prediction errors for positive and negative residuals differently. Ordinary objective functions such as the sum of squared residuals (SSE) are not appropriate in this case because we are dealing with an asymmetric pay-off (Amaldoss and Jain, 2002); not being able to drive is much more expensive (the average price $\overline{P_R}$ a rental customer pays for a drive is \$15 per hour) than the cost of selling electricity on the energy market (the average price that a fleet owner pays for charging $\overline{P_D}$ \$0.03 per hour (kWh) and the average price he earns for discharging $\overline{P_S}$ is \$0.05 per hour (kWh)). The MAW objective function penalizes forecasts according to the costs in each direction. While underpredicting storage is heavily penalized, as then storage is sold that could have more economically been rented out, overpredicting storage is encouraged, as the payoff is low compared to rental profits. The MAW objective function is determined as:

$$MAW = \frac{1}{n} \sum_{j=1}^{n} f_j(q, \widehat{q}) \tag{4.11}$$

$$with\ f_j(q, \widehat{q}) = \begin{cases} \widehat{q} * \overline{P_{S\ or\ D}} & \text{if} \quad q - \widehat{q} \geq 0 \\ \frac{q-\widehat{q}}{S_{max} kWh} * \widehat{q} * \overline{P_{S\ or\ D}} & \text{if} \quad q - \widehat{q} < 0 \end{cases} \tag{4.12}$$

where $\overline{P_{S/D}}$ is the average price of bids or asks. For a bid, to determine the capacity $q_{D,l,t}$ that EVs can still be charged with, with the MAW objective function, one needs to use the price a fleet owner pays for buying electricity $\overline{P_D}$. For an ask, to determine the capacity $q_{l,S,t}$ that EVs can discharge, with the MAW objective function, one needs to use the price a fleet owner earns for selling electricity $\overline{P_S}$. S_{max} is the maximum storage capacity of an EV, and $\overline{P_R}$ is the average rental price.

4.4.2 Determining the Price to Charge (P_D) and to Discharge (P_S)

The price for energy is determined dynamically by the day-ahead market equilibrium, as described in Section 4.2.4.

The pricing strategy needs to be scalable to millions of vehicles simultaneously to be able to make inferences on the market equilibrium with multiple fleets. We therefore developed a pricing strategy that can be computed efficiently. This strategy is based on two thresholds, which are optimized in the training period. If the market price exceeds the first threshold the fleet should sell electricity, if the price falls below the second threshold the fleet should buy electricity. This is implemented as a limit order (not a Stop-Order-Market). For more sophisticated pricing strategies we would like to refer to Chapter 2 and 3 of this dissertation.

Equation 4.13 specifies the bid price to buy electricity. By bidding the average electricity price P^* in the training period as limit price (the maximum price a buyer is willing to accept) to the market, our model ensures that the fleet owners bids are only matched with a seller if the buying price is below the mean clearing price during the training period.

$$P_{D,t}^{EV} = \frac{1}{t-1} \sum_{t=1}^{\tau} P_t^* \tag{4.13}$$

where τ is the duration of the training period in hours, $P_{D,t}^{EV}$ is the price of the bid submitted to the market by the EV fleet for hour t.

Conversely, Equation 4.14 specifies the ask price to sell electricity. The model adjusts the mean price P^* during the training period plus battery deprecation cost and submits these as ask limit prices (the minimum price a seller is willing to accept) to the market. That ensures that the fleet owner will at least break even when trading electricity, because the lowest selling price is always higher than the price at which the electricity is procured, including battery depreciation costs and conversion losses.

$$P_{S,t}^{EV} = \frac{1}{t-1} \sum_{t=1}^{\tau} P_t^* + b \tag{4.14}$$

where $P_{S,t}^{EV}$ is the price of the ask submitted to the market by the EV fleet for hour t, and b are the battery depreciation cost per kWh discharged.

4.5 Data

In order to evaluate the impact of our trading strategy, we use real-life market and mobility (rental) data, which we will discuss in this section. We consider the cities of Amsterdam with the districts {Zuid-oost, Oost, Zuid, Nieuw-West, West, Noord, Centrum}, Copenhagen with the districts {Indre By, Vesterbro, Frederiksberg, Osterbro, Norrebro, Amager, Bispebjerg, Valby, Bronshoj and Vanlose, Kastrup}, San Diego with the districts {ChulaVista, DownTown, MidCity, Hillcrest, Ocean Beach and Pacific Beach, MissionValley}, and Suttgart with the districts {Mitte, Nord, Sud, Ost, Wangen and Sindelfingen, Zuffenhausen and Bad Cannstatt, Feuerbach, Vaihingen and Degerloch, Sindelfingen, Plieningen, Esslingen}.

4.5.1 Day-ahead Electricity Market as Testbed

Electricity markets provide information about the prices and quantities of electricity sold, but also more fine-grained information about individual asks and bids. From these orders we extract preference information, which we use to build 'what if' scenarios to test how the market clearing reacts to increased demand induced by the presence of EVs. The market clearing price range determines the limits to profitability of the trading strategy. We use orders from the Northern European Nord Pool Spot electricity market (`www.nordpoolspot.com`), because it is representative of many energy markets in the future due to its high share of renewable energy sources in the electricity mix and it is the largest energy market in the world. Using detailed data on actual bid and ask from a market allows us to mimic how bids and asks by fleet owners would do on this market. In this way one can observe the effect on the market clearing of additional bids and asks from EVs that are part of a VPP. It is important to use the empirical bid and ask data rather than stochastic processes, because the decision processes of market participants change when they reevaluate their options and are confronted with new choices such as storage provided by EVs (Shen and Su, 2007). Even though all 2000+ market participants are price takers, it is desirable to have an insight into their behavior. We do this by using their actual asks and bids, add the asks and bids from fleet owners to them and then clear the market.

The Nord Pool Spot ELSPOT market is a day-ahead market for the Scandinavian and Baltic region where about 360 buyers and sellers trade on average over 40,000 MWh of electricity per hour (one fleet of 500 EVs can store approximately 0.02% of this electricity). This includes more than 2000 asks or bids hourly, hence a time interval t of one hour. The market is operated according to the mechanism outlined in Section 4.2.4. The Nord Pool Spot Power Data Services kindly made the individual asks and bids available for research purposes. Their data consist in total of about 8 million bids and asks over the 365 day period January to December 2013. From this data we reconstruct the trading settlements for all 8760 (=365 days * 24 hours) clearing events. Figure 4.6 shows two exemplary clearing events; the clearing event on the left shows the demand and supply functions for the 15th of July between 0-1 AM.

This particular supply curve consists of 582 asks from sellers. Here is an example how the asks in the market look like:

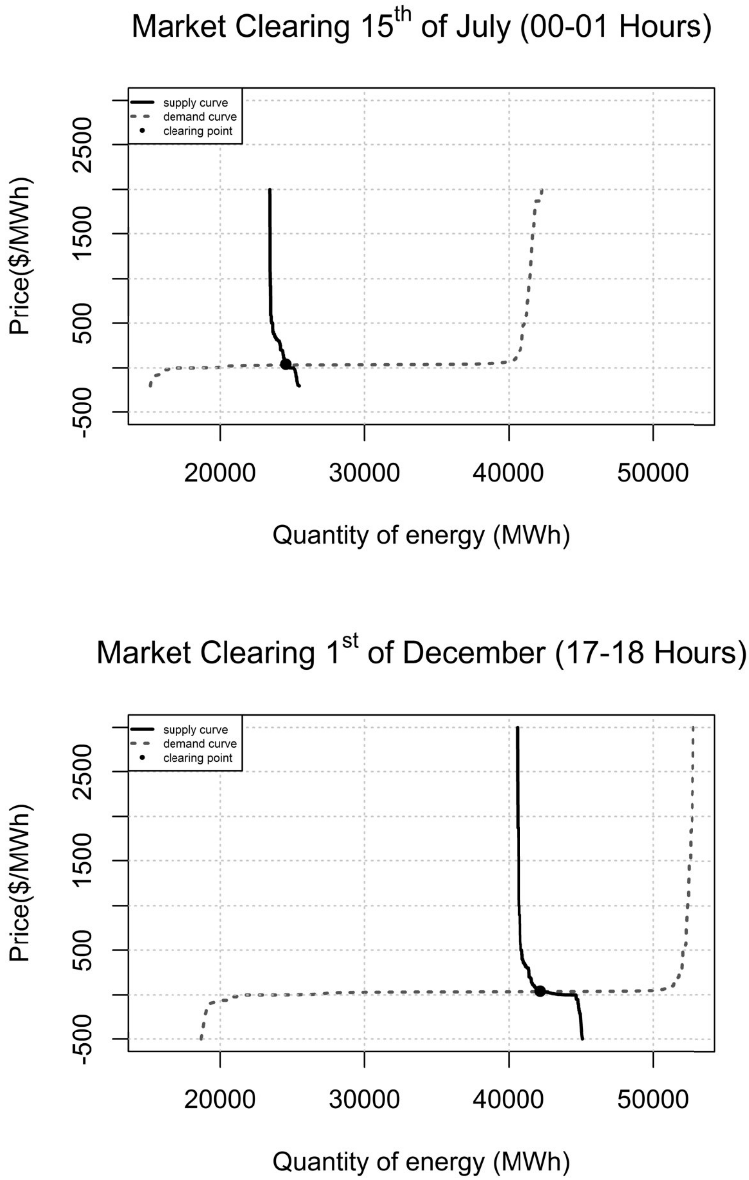

Figure 4.6: Demand and supply curves for two specific dates. The curves consist of individuals asks and bids taken from the Nord Pool Spot market, which we complement with additional bids from the EVs, the Prosumer Trading Strategy.

$Q_S^1 = 15,114.01 MWh,\ Q_S^2 = 15,121.58 MWh,\ \ldots,\ Q_S^{582} = 42,304.32 MWh;$
$P_S^1 = -200 \frac{\$}{MWh},\ P_S^2 = -191.06 \frac{\$}{MWh},\ \ldots,\ P_S^{582} = 2,000 \frac{\$}{MWh}.$

The demand curve consists of 314 bids from buyers. Here is an example how the bids in the market look like:
$Q_D^1 = 23,432.43 MWh,\ Q_D^2 = 23,433.45 MWh,\ \ldots,\ Q_D^{314} = 25,477.12 MWh;$
$P_D^1 = 2,000 \frac{\$}{MWh},\ P_D^2 = 1900.76 \frac{\$}{MWh},\ \ldots,\ P_D^{314} = -200 \frac{\$}{MWh}.$

The clearing point indicates that at this date 24,550 MWh are sold at a price of $39 \frac{\$}{MWh}$. Similarly, the clearing event on the right for the 1st of December from 5-7 PM consists of 704 asks and 396 bids. These market participants traded 42,200MWh at a unit price of $41 \frac{\$}{MWh}$ at that time interval. The clearing point is calculated as the double auction described in Section 4.2.4. We then add the orders from the EV fleet owner (see Section 4.3.1) to the market to evaluate the profits for fleet owners. We also analyze the influence that more than one fleet has on the clearing price.

4.5.2 Electric Vehicle Driving Profiles

The availability of idle EVs is critical for properly functioning VPPs. For the forecasting model developed in Section 4.4.1, we have gathered driving data from Daimler's EV car-sharing service Car2Go (`www.car2go.com`) in San Diego (300 EVs), Amsterdam (300 EVs), and Stuttgart (500 EVs) and from BMWs car-sharing service DriveNow (`www.drive-now.com`) in Copenhagen (400 EVs). The dataset from Copenhagen is unique and especially relevant for the results as it is the only city which is part of the Nord Pool spot market. The data gives us unique insights in driving patterns and preferences about large fleets of real EVs and their drivers. In the car-sharing services from Car2Go and DriveNow customers can rent out EVs without reservations, pay by the minute, and drop them off at any location within the city boundaries. Daimler and BMW currently consider merging Car2Go and DriveNow highlighting the similarity of the two services. The Car2Go and DriveNow data includes the following information about idle cars: current time which we will use to get the hour (t), vehicle ID (i), GPS coordinates latitude, GPS coordinates longitude, address, state of charge (S), whether it is parked at a charging station, and whether the car is currently charging. All of this data is available on the web in real-time for all 1,500 EVs (I). Daimler AG gave us permission to access a private API to harvest this data every 5 minutes. For DriveNow we use a self-built web scraper that downloads the data about the EVs every 5 minutes. See Table 4.2 for sample data about an EV. The information about these cars is stored in a database and complemented with data on charging station locations. Access to information about the charging state of each car and the

Table 4.2: Sample data of an EV. Note that only idle cars are shown; the change in battery status and time in the last row indicates that the EV was not parked, and therefore rented, in the meantime.

Time t	**ID** i	**Address**	**SoC**	**Chargingspot**	**Charging**
13.05.2014 19:25:00	S-GO9	Sommerrainstr. 90 70374 Stuttgart	96	TRUE	FALSE
13.05.2014 19:30:00	S-GO9	Sommerrainstr. 90 70374 Stuttgart	96	TRUE	FALSE
13.05.2014 20:30:00	S-GO9	Im Buchwald 19 70186 Stuttgart	85	FALSE	FALSE
..					

location of charging stations enables us to calculate both how much electricity each EV can store, and how much electricity it can sell from each location. We collected the data for Stuttgart from November 2013 till December 2014, and for San Diego and Amsterdam from March 2014 till December 2014. We have not been able to gather data between March 31st and April 20th 2014 due to a server error of our web scraper. The data for Copenhagen was collected at a later point from August till December 2016 in order to validate our findings with a city within the Nord Pool Spot region. Since DriveNow is a different operator and the user base is relatively new (they started operating in 2015 in Copenhagen, while Car2Go started in 2011 and 2012 in the other cities) some of the differences in patterns may not be directly comparable and therefore need to be interpreted with caution. However, as our model uses a rolling time horizon for the training period it will quickly pick up changing behavioral patterns over time. We use a $\tau = 60$ day training period because we have 14 month of data; that way we can consider a whole year and have 60 days to train our forecasting for the first day.

All EVs are subcompact cars. The EVs from Car2Go are Smart Fortwo electric drives with a 16.5 kWh battery (S_{max}), the EVs from DriveNow are BMW i3 with an 18.8 kWh battery (S_{max}). See Online Appendix A for a sensitivity analysis on battery size. Figure 4.7 shows the percentage of idle EVs over the course of a day for Stuttgart. As expected, the data shows that fewer EVs are idle during the day than during the night, and this is especially pronounced during the afternoon and evening rush hours, when on average 60% of EVs are idle. There is also a rental peak during the morning rush hour at 9 AM, but this peak is relatively small compared to those in the afternoon and evening. Apparently, car-sharing is used more frequently after work, and not as much for commuting or during office hours. The lowest observed

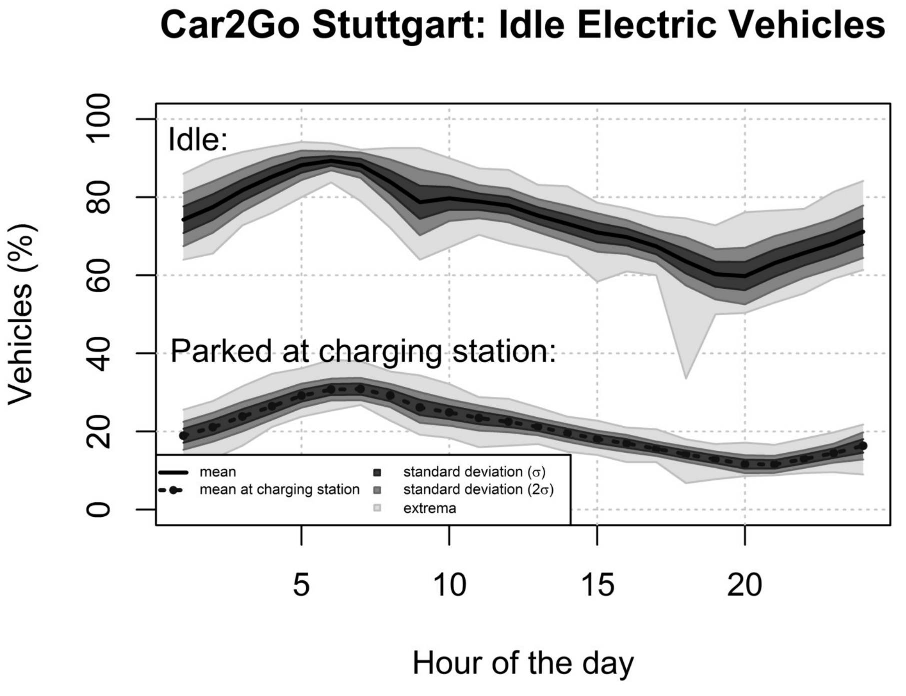

Figure 4.7: Average driving patterns with standard deviation from Car2Go's car-sharing fleet. EV rentals are particularly concentrated around evening hours.

idleness of EVs over the whole period is 34%, which occurred in the afternoon rush hour. During the night hours almost all EVs are idle; at its extreme 94% of the cars were not being used, which creates potential room for trading with and charging EVs. Figure 4.7 also shows the percentage of idle EVs that are connected to a charging station. On average, one third of the EVs are parked at a charging station, but over the course of a day the trend remains similar. Only EVs parked at a charging station can be used to provide storage on the energy market in our model. As in the future one can expect even more charging stations, the profits that we show are possible for fleet owners now, will likely be even higher.

This dataset is unique in the sense that there are virtually no other data sources of this size on EV driving data which include the location and state of charge.

4.5.3 Battery Costs and Conversion Losses

As the developments in battery technology are crucial to determine profitability (Schill, 2011) yet difficult to predict, we consider three scenarios. The third scenario is based on the current battery price of approximately 150 $\frac{\$}{kWh}$ capital costs[2] depreciated over 3000 life cycles[3]. After these cycles the current battery technology is able to store only 85% of the original storage capacity and is considered obsolete. The corresponding battery depreciation cost (b) are $\frac{150\frac{\$}{kWh}}{3000\ cycles} = 0.05\frac{\$}{kWh} = 50\frac{\$}{MWh}$. The second scenario is based on the assumption that capital cost decrease to $70\frac{\$}{kWh}$ while the number of cycles increases to 7000, with a resulting battery depreciation cost (b) of 10 $\frac{\$}{MWh}$. The first scenario serves as a benchmark to show the extreme case of no battery cost. For the VPP application it is particularly important to make accurate cost allocations, so as not to artificially increase the costs of driving. Whenever a fleet owner trades, he or she needs to take into account the wear-out depreciation costs of the battery capacity used for that transaction. We create corresponding depreciation cost (b) scenarios, which amount to 0 $\frac{\$}{MWh}$ in the base case scenario 1, to 10 $\frac{\$}{MWh}$ in scenario 2, and 50 $\frac{\$}{MWh}$ in scenario 3. Furthermore, about 3 to 4% of the energy is lost from the conversion efficiency (e_c) when the EV is being charged (Reichert, 2010). When energy is delivered to the grid from the EVs battery, 2.4% of the energy is lost (e_d). Every time the VPP is used we have to account for these costs to arrive at accurate estimates of the actual benefits. With the direct current lines that are being planned these conversion losses would be reduced, enhancing our business case.

4.6 Analysis: Triple Bottom Line

In this section we analyze the results of our simulation with the trading strategy for EV fleet owners. We evaluate and explain the effects of VPPs that consist of EVs for fleet owners and on society in terms of the triple bottom line. First, we evaluate the financial viability under competition (profit) for the fleet owner, we then analyze the effects on the electricity price for consumers (people), and finally we illustrate the impact on carbon emissions (planet).

[2] `http://www.forbes.com/sites/samabuelsamid/2015/10/28/lg-chem-may-be-on-the-verge-of-dominating-ev-battery-industry/#52d4d003144d` [Accessed: 10-Feb-2016]

[3] `http://www.saftbatteries.com/force_download/li_ion_battery_life__TechnicalSheet_en_0514_Protected.pdf` [Accessed: 10-Feb-2016]

4.6.1 Profit: Fleet Perspective

For the fleet owner it is important that EVs are optimally allocated among the states of charging, discharging (rentals), discharging (grid), and being idle. This is important because it affects the profits of the fleet owner. We analyze the profits of the allocation, and how the profit is influenced by fleet size and competition.

4.6.1.1 Allocation to States: Charging, Discharging (rentals), Discharging (grid), Idle

Our model allocates the EVs to the four states of charging (adding inventory), discharging for renting (decreasing inventory), discharging to the grid (decreasing inventory), or being idle (no change in inventory) to maximize the fleet owner's profits. In particular, our model forecasts the electricity available for discharging based on the previous $\tau = 60$ days per location. For example Figure 4.8, 4.9, and 4.10 show the forecasts for the districts Mitte, Ost, and Wangen in Stuttgart. The Figures show a fitted model with the sum of squared errors (SSE) and how it predicts over a test period. However, we apply the mean asymmetric weighted (MAW) objective function, developed in Equation 4.11 to make sure that only in very few instances our model predicts to discharge an EV when it would have better been rented out (underpredicting). Given the cost of a rental relative to the electricity cost the MAW model predicts the electricity available for discharging more conservatively. Only on one day out of the predicted days in Figure 4.8, 4.9, and 4.10 on the noon of the 26^{th} of July 2016 in Stuttgart Mitte our model underpredicted the amount (marked in red in Figure 4.8), where more EVs should have been reserved for rentals than our model indicated. Note that the opposite, where our model overpredicts there was less storage available than there was in reality, happens frequently (marked in grey in Figure 4.8, 4.9, and 4.10). However, due to the asymmetric cost this type of error is not as costly and fleet owners only lose out on a few cents for the overpredicting because doing that decreases the chance that one of these EVs cannot be rented out for much more money. This is why the MAW based model is more appropriate then a model fitted with SSE. The Figures 4.8, 4.9, and 4.10 also show that the daily patterns depend on the district. For example, Figure 4.8 shows a daily pattern in Stuttgart Mitte where much storage is available during noon, while in Figure 4.9, and 4.10 in Stuttgart Ost and Wangen more storage for discharging is available during the night. This is beneficial for the trading decisions of the fleet owner, as he has storage available to trade more or less evenly distributed over the day from the various districts. The

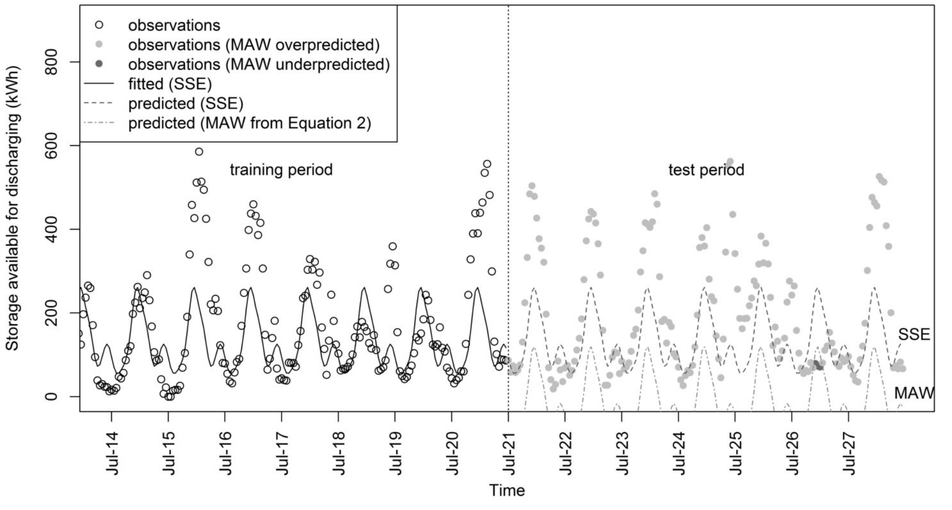

Figure 4.8: Snapshot of the rolling time window for the 21st of July for the prediction of available storage for discharging in the Mitte district of Stuttgart. The daily recurring pattern indicates that there is a lot of idle capacity available during the day. Underpredicting is very costly and happens only during the noon of the 26th of July 2016 with the MAW model.

difference between Stuttgart Ost and Wangen is that Ost has a higher variability in storage availability than Wangen.

The amount of EVs that should be allocated to the charging state is determined in the same way as for discharging with the MWE objective function.

The other two states, idle and discharging for renting, are the EVs that remain. These EVs are idle until a customer decides to rent them. In the next section we will have a look at how these allocation decisions pay off for the fleet operator financially and benchmark these profits.

4.6.1.2 Benchmarking our Model

The allocation of EVs to the four states pays off for EV fleet owners. In all four cities under consideration EV fleet owners make more profits when applying our model as compared to only renting out their EVs. Figure 4.11 shows the annual profits from rentals with a flat electricity price, the annual profits from rentals including our model with uncertainty about the day-ahead rental demand and variable day-ahead electricity prices, and a benchmark with perfect information on rental demand and known day-ahead electricity prices. The benchmark shows how much annual profit

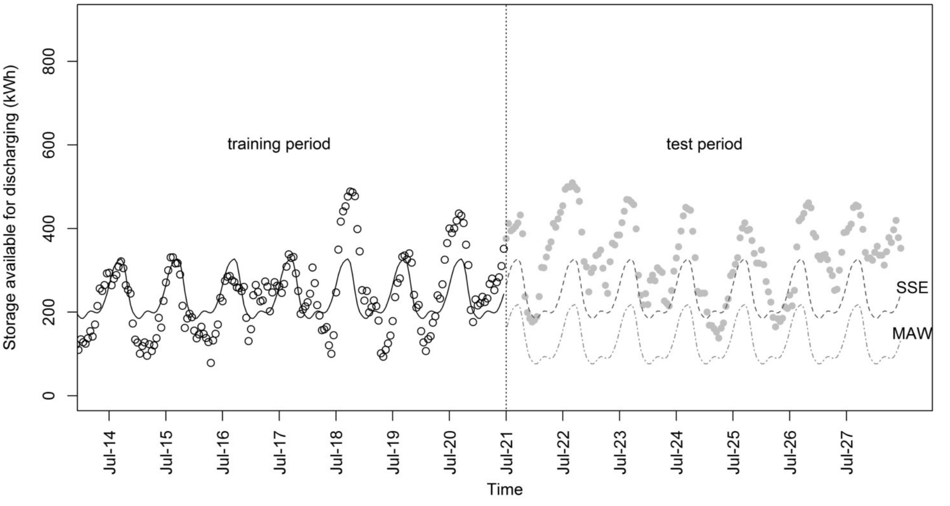

Figure 4.9: Snapshot of the rolling time window for the 21st of July for the prediction of available storage for discharging in the Ost district of Stuttgart. The daily recurring pattern indicates that there is a lot of idle capacity available during the night.

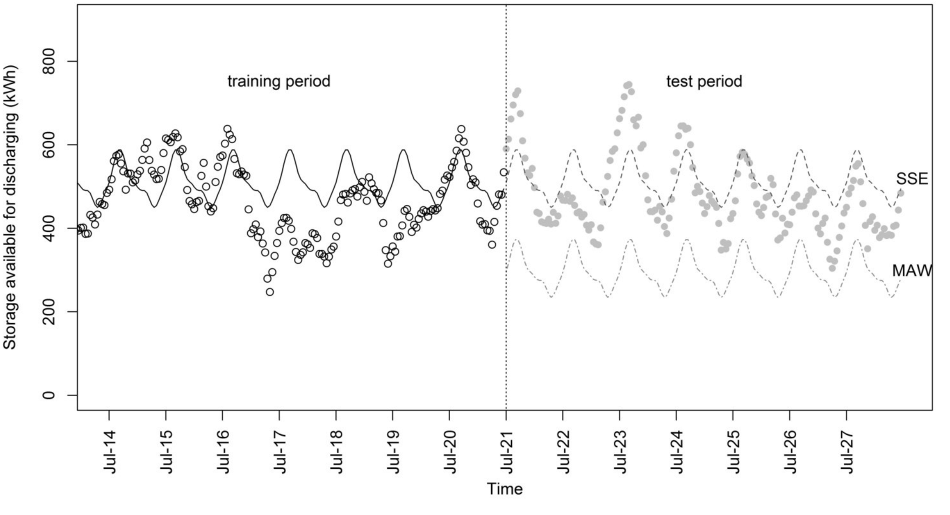

Figure 4.10: Snapshot of the rolling time window for the 21st of July for the prediction of available storage for discharging in the Wangen district of Stuttgart. The daily recurring pattern indicates that there is a lot of idle capacity available during the night but there is less peakedness compared to the Ost district.

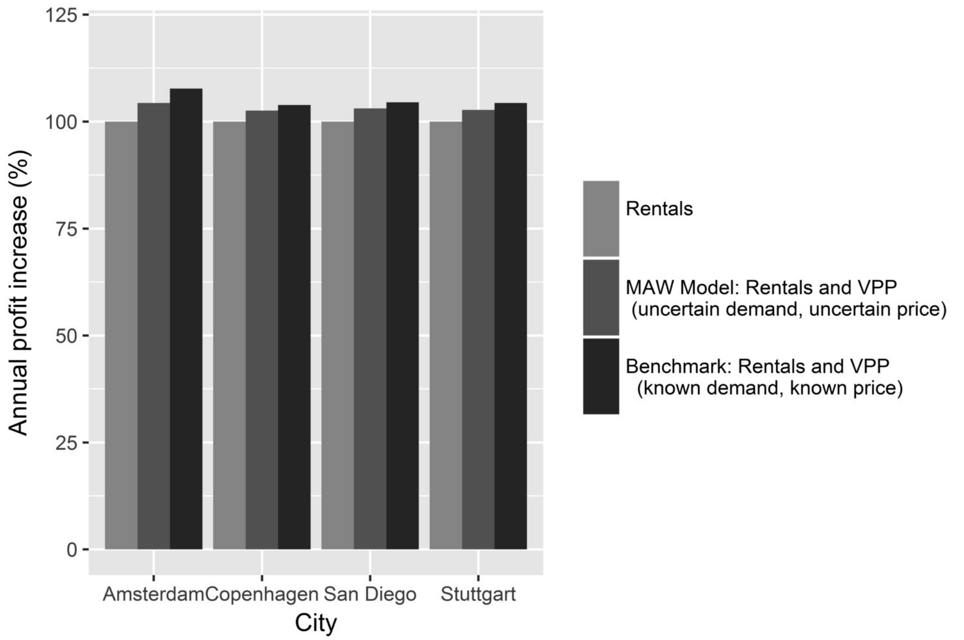

Figure 4.11: Comparing the performance of our model to the rental base case and a benchmark with perfect information on when and where EVs are rented in advance across Amsterdam, Copenhagen, San Diego, and Stuttgart with no battery depreciation cost (scenario 1).

could have been achieved if we had known perfectly in advance where and when the rental transactions will take place. If a car-sharing fleet, like Car2Go or DriveNow, would like to offer their EVs to users that rent EVs spontaneously, then one can only get close to the benchmark, such as our model, but never reach it because of uncertainty. With the current pricing scheme for rentals and the current variable day-ahead electricity prices fleet owners earn most profits with their conventional rental business model. However, Figure 4.11 shows that our model with VPPs consistently outperforms the rental only case and comes close to the benchmark. Across all cities under consideration we see an annual profit increase of between \$173 and \$252 (2.5% and 4.3%) compared to the benchmark of between \$262 and \$447 (3.9% and 7.7%) per EV. In the next section we show how the annual profit is influenced by fleet size and competitive effects.

4.6.1.3 Fleet Size and Competitive Effects

Unless fleet owners know where and when EVs will be rented they need to make accurate predictions for it. As the fleet size increases it becomes easier for fleet owners to forecast at which locations idle EVs can be reserved for charging or discharging. Figure 4.12 shows how the profits per EV in Copenhagen increase as the number of EVs within a fleet increases. The annual profit per EV increases quite steep in the beginning between 25-300 vehicles and then gradually levels off around 400-500 vehicles. This trend suggests that it is best for fleet owners to have a fleet which is as large as possible for VPP purposes. However, competition has the opposite effect; the more VPPs of EV fleets compete on the market leaving all other bids and asks as is, the more the arbitrage opportunities between low and high prices are reduced. Figure 4.13 shows how the trading profits and savings from charging change as a function of the percentage of the market share that EVs have relative to those of vehicles with internal combustion engines. We assume perfect competition due to more than 2,000 market participants, where several independent fleet owners of 500 EVs participate in the electricity market as VPP, too. These independent fleet owners submit bids and asks to the market. Equilibrium prices are determined by supply and demand from many actors. No single participant can set the prices for electricity. However, together actors do have an effect on the market. As illustrated in Figure 4.13, the market experiences diminishing returns for every additional EV that enters the market until the EV market share reaches 20%. The figure shows that fleet owners make high profits when the share of EVs in the market is low (<20%). Under these circumstances each fleet owner makes between \$173 and \$168 annually per EV, of which between \$20 and \$23 dollars can be attributed to discharging profits and the rest comes from savings from cheaper charging.

When many EVs charge at low prices and sell at high prices, the price difference for arbitrage decreases. This effect rewards early adopters with premium returns. When the market share of EVs is above 20% virtually all the additional profits for fleet owners come from charging EVs at a cheaper than average rate. Comparing these findings to those presented by Peterson et al. (2010) and Schill (2011), who found profits of \$16-96 and \$135-151 respectively, we conclude that the findings are similar for a low market share of EVs. This is an important contribution because, unlike previous research, we included in our forecasting model uncertainty over when EVs are likely to be used and yet we were still able to demonstrate that this type of trading strategy was profitable.

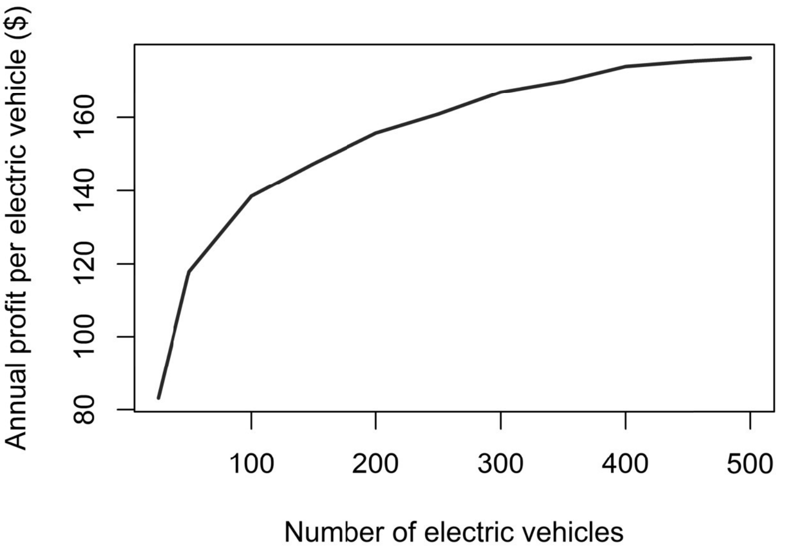

Figure 4.12: Fleet size increases profits significantly for small fleets, but levels off at higher numbers (example from Copenhagen).

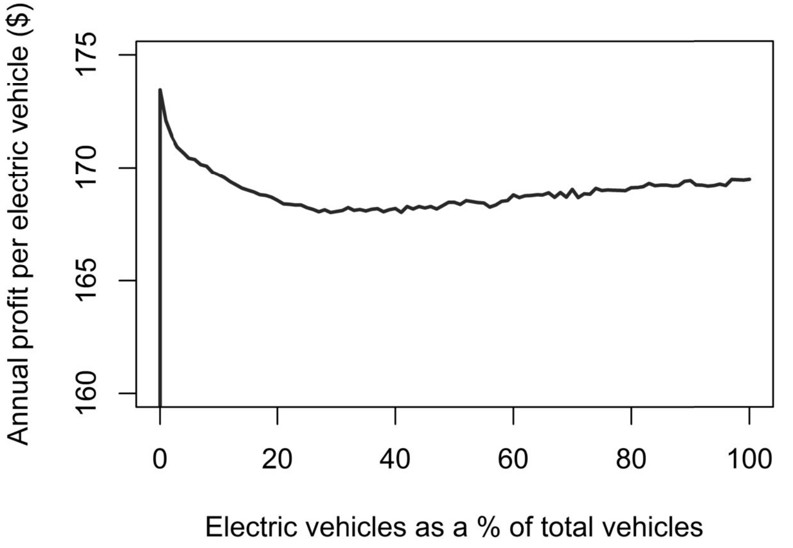

Figure 4.13: Adverse effects of competition on annual profit per electric vehicle. When the market is saturated with EVs, due to for example other fleet owners engaging in a similar strategy, the profits per EV decline (example of Copenhagen).

4.6.1.4 Battery Cost Effects

It is surprising that battery depreciation costs have a marginal impact on the profitability of the trading strategy. The total profits for the fleet owner from the first scenario with no battery depreciation cost are only 9% lower than in the third scenario with 50 $\frac{\$}{MWh}$. This can be explained by the individual trading orders. The majority of orders are high-volume trades with low profit margins that represent only a small share of the total annual trading-only profits. Most of the trading profits are generated from just a couple of asks that involve small quantities but have an extremely high arbitrage margin so that battery depreciation costs are of relatively little importance. We therefore find that battery depreciation plays a less important role for our strategy. This is different for other strategies, such as for example the one considered by Peterson et al. (2010). These differences in findings may also be due to market differences. But in the context of the increasing share of renewable energy sources in markets worldwide, the Nord Pool Spot market is a more valuable source of information. See Online Appendix B for a sensitivity analysis of the market price.

4.6.2 People: Societal Perspective

In contrast to the diminishing returns under competition for fleet owners there are increasing benefits for all consumers of electricity in a society when more EVs participate in VPP trading. Market prices decrease for consumers and the operation of power plants is optimized.

As fleet owners make additional energy available to the market, the supply increases while demand remains the same, and this has the effect of lowering the clearing price. However, when fleet owners charge their EVs for use as VPPs, the demand increases while supply remains the same, affecting the clearing price adversely for consumers. Both also have an effect on the overall system cost because the efficiency increases due to a peak-to-average ratio (PAPR) decrease. The PAPR is a performance measure of the utilization of power plants; to increase the efficiency of the system, the PAPR must be lowered. See Online Appendix C for a profound explanation of PAPR. To investigate the effects of this, the prices for electricity weighted by their traded quantities and PAPR are measured in our simulation without VPP and the results are then compared to the same simulation with a paired t-test[4], but with VPPs.

Figure 4.14 shows the electricity price reduction for all consumers of electricity in a society as a function of the EV market share. The figure suggests that the

[4] As we are dealing with a huge number of observations (above 30,000), the results are highly significant; we do not therefore report p-values in the remainder of the paper.

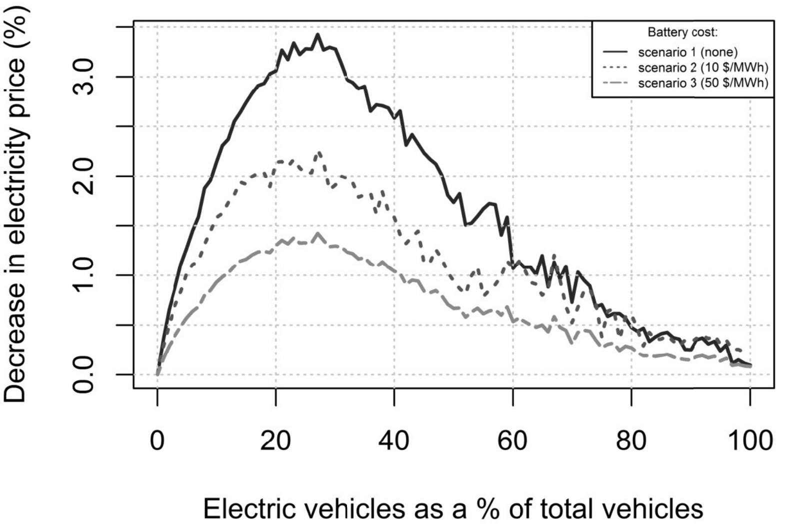

Figure 4.14: Electricity price reduction as a function of EV penetration in Denmark. The effect is more pronounced at a low EV market share.

average wholesale market price is significantly lower when VPPs are available, even though this depends on the market share of EVs to a large extent. The effect on the electricity price is most pronounced when the market share is between 5% and 60%, even though the magnitude depends on the battery depreciation costs. There is somewhat less of a decrease in price when there are higher battery depreciation costs and increasing competition, because in these conditions fewer trading orders are made. However, under the best conditions (5%-60% market share) the wholesale electricity price is reduced by 1.5% to 3.4%. These reductions are significant for all three battery depreciation scenarios at the 1% significance level, when compared with a two sample t-test assuming unequal variances. In contrast to this, previous research found a 14% reduction in energy prices (Vytelingum et al., 2011). The difference can be explained by car usage. Whereas batteries in the previous study are always available for balancing purposes, the batteries in this research are constrained by the trade-off between driving and balancing the grid.

Another important aspect of this business model is the impact it is has on the electricity price variability. When energy is supplied to the grid at peak prices and used at low prices, electricity price volatility is reduced; which is measured by the peak-to-average power ratio. A lower ratio leads to a more efficient electrical grid. Both a two sample t-test which assumes unequal variances for PAPR and a two sample F-test for variances which compares the volatility of clearing quantities with and without VPPs show that PAPR and the variance is significantly reduced at the 1% significance level. This effect has a beneficial impact on the grid for two reasons. First, it optimizes the overall utilization of power generation sources by increasing the competition in operating reserve markets, making the grid more efficient. And second, a lower PAPR means that investment in expensive infrastructure can be reduced.

4.6.3 Planet: Carbon Emissions

EVs have 10%-25% lower global warming potential than combustion engine vehicles when accounting for all lifecycle emissions (Hawkins et al., 2013). This takes the additional emissions arising during the battery production into account, which are on average 15% of an EVs lifecycle emissions (Notter et al., 2010). In our study we seek to isolate the effect of the VPP emission reductions and explicitly exclude emission reductions as compared to combustion engine vehicles and increases from producing vehicle parts and batteries. This isolated effect can then be included by other studies with a broader scale. Our VPP-based trading mechanism reduces CO_2 emissions, as we will now explain in detail.

For each hourly time interval t there is an amount of electricity x_t that is produced by renewable energy. As renewable energy is prioritized due to low marginal cost in the merit order, any demand that exceeds x_t will be met with non-renewable energy sources. In the opposite case, when x_t exceeds the demand, the production of renewable energy needs to be curtailed. Curtailment means that for example wind turbines that have enough wind to produce electricity need to be shut down.

Our trading strategy tends to buy electricity to charge the EVs when there is less demand than renewable energy production. Therefore, it reduces the need to curtail renewable energy sources, and feeds this electricity back to the grid at a point in time when the demand exceeds the renewable energy production. This has a positive effect on the total $\mathrm{CO_2}$ reduction of the energy system.

To assess the quantity of $\mathrm{CO_2}$ reduction of our trading strategy we measure the quantity of energy that did not need to be curtailed and instead replaced a non-renewable energy unit at a later point in time. For this analysis we consider the amount of renewable energy x_t that is generated in each point of time t, the we consider the total demand for electricity at point t, we consider the amount of energy that was charged to the electric vehicles at point t, and the amount of energy that was discharged from the batteries to the grid at point t.

We find that in Denmark, if 250,000 electric vehicles (10% of all vehicles) were to participate in the electricity market as described in this paper, the curtailment of wind energy could be reduced by 25,000 MWh annually (36%). With 750,000 electric vehicles (30% of all vehicles), the grid could even avoid curtailment of 66,000 MWh annually (97%). This reduces the amount of CO_2 emissions, as the wind turbines can run at full capacity at all times.

4.7 Conclusions and Future Work

Increasing volatility in energy production due to distributed sources of renewable energy creates challenges, but also provides scope for new business models in the future. We have presented a strategy for a business model which is both profitable for electric vehicle fleet owners and sustainable. Based on a highly intelligent model that offers advantages for fleet owners, electricity consumers, and the environment, our model allows fleet owners to charge their electric vehicles more cheaply, use their storage capacity for arbitrage trading, and rent them out as usual. Our model recommends the optimal states for all electric vehicles in the fleet across charging (adding inventory), discharging for driving (decreasing inventory), discharging to the grid (decreasing inventory), or being idle (no change in inventory). Fleet owners make a trade-off between a class of demand where location matters (drivers want a car to be close to their place of departure) for a class of demand where location does not matter (vehicles can discharge to the grid from any capable charging point). We have developed a mean weighted average (MAW) objective function that makes an optimal tradeoff between the asymmetric cost of renting, charging, and discharging at different city districts in Amsterdam, Copenhagen, San Diego, and Stuttgart. A sinusoidal model is best suited to predict the optimal states as it captures the daily and weekly recurring patterns observed in electric vehicle car-sharing fleets. In particular, the model is very well suited to predict demand with unique characteristics across different districts of a city. We show that using our model enhances the profits of electric vehicle fleet owners significantly; they can earn between \$173 and \$252 (2.5%-4.3%) more profits annually per electric vehicle under the current Noord Pool Spot market prices. These profit ranges are similar to the findings by Peterson et al. (2010) and Schill (2011), but it is an important contribution because our MAW model accounts for uncertainties of EV rental demand and uncertainty of variable prices on a day-ahead market. While we have proven the usefulness of our model in a car-sharing setting, it can also be extended to the caching literature. In particular, our MAW model with asymmetric payoffs could prove useful in differentiating valuable content, for example commercials that earn more profits than other content.

We applied analytics to big energy data from energy markets and electric vehicle fleets in order to create a smart market for electricity. We have demonstrated that optimizing this market from a profit-maximizing perspective has desirable externalities for the triple bottom line of people, planet, and profit. For people, there are welfare gains for individual consumers and society as a whole due to reductions in the average electricity price for all consumers in a society by up to 3.4% and decreases the peak-to-average ratio. This saves important raw materials such as copper. We have also presented evidence that our trading strategy could bring about a reduction in carbon intensity. This could lead to a decrease in CO_2 emissions as renewable energy sources would not need to be curtailed. We find that if 30% of all vehicles in Denmark were electric vehicles, they could avoid curtailment by 97%. Depending on battery technology developments, fleet owners can make a significant profit with this business model, though, the level of profit decreases as more vehicle fleet owners compete on this market.

In our current model we focus on idle electric vehicles only. Future research could elicit the valuations and preferences of consumers relating to electric vehicle availability. Consumers might, for example, decide to postpone trips in the electric vehicle if they can make a good arbitrage deal. An alternative for fleet owners would be to offer service levels for electric vehicle availability in which they segment customers according to their flexibility. Another rewarding topic for future research would be to look at virtual power plants as generators in ancillary service auctions. Significantly higher peak prices on the ancillary market are attractive to virtual power plants. The study of incentive structures and mechanisms of electric vehicle storage in micro grids is another promising field of application for virtual power plants because power generation, storage, and charging needs to be micromanaged. Individual homes that have solar panels or small windmills combined with an electric vehicle and other storage capacity could function as self-sufficient microgrids, and smart electric vehicle charging could be used to help prevent losses in solar and wind parks. Future research should also consider the implications that technological paradigm shifts such as inductive charging and autonomous driving will have.

Chapter 4: Appendix

Appendix A. Sensitivity Analysis: Battery Size

The analysis is based on the battery size of the actual Smart ForTwo EVs with a capacity of 16.5 kWh and the BMW i3 with a capacity of 18.8 kWh, both with a range of approximately 70 miles. However, as new middle class EVs with wider range, like the Tesla model 3 with a 215 mile range will enter the market in 2017, we also need to consider the case with larger batteries. We therefore conducted a sensitivity analysis on how the change to larger batteries will affect our findings. This analysis provides insights into the effects of using 50 kWh (212 miles) and 100 kWh (424 miles) batteries instead. Currently, we do not have data on batteries of this size, but we expect people to use this capacity to make longer trips. We scale up the usage of the EVs linearly (for example at a state of charge of 50%, usage becomes $0.5*16.5kWh = 8.25kWh, 0.5*50kWh = 25kWh, and 0.5*100kWh = 50kWh$), which leaves relatively more capacity for trading. We discuss battery scenario 1 without battery cost, as the other scenarios behave similarly. As expected, the additional trading profits per EV scale linearly to the battery size. The energy price decrease caused by our trading strategy decreases even further by 4.0% and 4.2% when the cars would possess 50 kWh and 100 kWh batteries respectively as compared to the a 3.4% reduction at its peak from real 16.5 and 18.8 kWh batteries initially. The overall electrical grid efficiency remains the same also if the battery size is scaled up. However, initial benefits are reaped much faster at low EV adoption rates (<7%), while at a larger adoption rate the grid efficiency increases more slowly. Similarly to the grid efficiency, the battery increase does not change the CO_2 emissions for high adoption rates, but benefits are reached already at smaller adoption rates.

Appendix B. Sensitivity Analysis: Market Price

Our analysis of the fleet owners profits are based on the market prices of the ELSPOT market over the specified time period. However, it is possible that in other markets and in the future these price levels change. Therefore, we have conducted a sensitivity analysis to assess the effect of 5% and 10% higher and lower electricity clearing market prices on the trading strategy. As the profitability is dependent on the arbitrage differences between prices over time, we use a multiplicative error function to scale the error stochastically (Sancho et al., 1982). We do this by multiplying the clearing price with a normally distributed error term and add it to the price to capture changes to the variability of the price in Equation 4.15. And then we do the same steps from the simulation as described in Section 4.4 to evaluate the profitability for fleet owners.

$$P^{sensitivity} = P^*(t) + P^*(t) * \epsilon \tag{4.15}$$

where ϵ is a normal distribution $\epsilon \sim (\mu, \sigma^2) with (\mu, \sigma^2)$ equal to (0.05, 0.01), (0.1, 0.02), (-0.5, 0.01), and (-0.1, 0.02). Note that the market price can be negative in electricity markets, so we do not apply non-negativity constraints.

A larger variance in the prices increases the potential for arbitrage. We find that an increase in the market clearing price differences by 5% and 10% increases the profits of our trading strategy by 6% and 9% respectively. In contrast, a decrease in the market clearing price differences by 5% and 10% decreases the potential for arbitrage. If we decrease the market clearing price differences, then the profitability of the trading is reduced by 5% and 7% respectively. This shows that the model is still profitable for small changes (±10%) in the market clearing price and its variability.

Appendix C. The Effect of Large Scale Adoption on the Electricity Market

Both selling and buying of fleet owners has an impact on the clearing price and quantity for that hour; but the impact of individual fleet owners with fleets of 500 EVs or less is marginal and can therefore be considered to be price takers. However, if there are many fleets competing on the market, together they have an influence on the market price. On the one hand, they place asks on the market to discharge the EVs, increasing the supply and leading to a larger clearing quantity and a drop in price. On the other, when fleet owners place bids on the market to charge the EVs, the demand increases, thus raising both the clearing quantity and the price. These asks and bids also have an influence on the peak-to-average power ratio (PAPR). The PAPR is a performance measure of the utilization of power plants; to increase the efficiency of the system, the PAPR must be lowered. It is calculated as:

$$PAPR = \frac{\mid Q_{peak} \mid^2}{\sqrt{\frac{\sum_{j=1}^{n} Q_j^2}{n}}} = \frac{\mid Q_{peak} \mid^2}{Q_{rms}^2} \tag{4.16}$$

where Q_{peak} is the highest quantity cleared in the market and Q_{rms} is the root mean square of all cleared quantities. The PAPR is the ratio between the maximum and the average energy demand. As the grid needs sufficient power plants to serve the maximum energy demand, most of these are idle during average demand. Decreasing the PAPR decreases the need for idle capacity. In the analysis we will investigate how adding EVs influences the efficiency of the system as a whole with the PAPR measure.

Chapter 5

Conclusions

In this dissertation we investigated how electric vehicle fleets can increase their profits by selling idle storage capacity as virtual power plants on energy markets. Therefore we have developed a demand prediction model in Chapter 2 based on which fleets can preposition their vehicles to maximize service levels at minimal cost. In Chapter 3 we apply the demand prediction model to participate in pay-as-bid frequency regulation auctions, the secondary operating reserve markets, with virtual power plants of electric vehicles. We show that this is already profitable today but will be even more profitable as the demand for balancing resources increases while the supply decreases as fossil fuel based power plants are taken of the grid. We also show how the density of charging infrastructure moderates this outcome. Lastly, in Chapter 4 we apply the demand prediction model to schedule the charging process of electric vehicles according to the double auction of day-ahead markets to save both money and CO_2 emissions. We also analyzed bids and asks to make inferences on the impact of large number of electric vehicle fleets on the energy market. Our contributions can help with new solutions, as they are profitable, as well as good for the planet and people. This is especially important in light of the withdrawal of the U.S. President Donald Trump from the Paris Climate Agreement. To summarize, we have developed:

[1] a highly accurate model to predict mobility demand and preposition one-way mobility fleets (Chapter 2).

[2] pay-as-bid auction (operating reserve market) with a machine learning based pricing strategy for virtual power plants of electric vehicles and a sensitivity

analysis of how an increase in charging infrastructure influences the profits of virtual power plants (Chapter 3).

[3] double auction (day-ahead market) with a sinusoidal based pricing strategy of virtual power plants of electric vehicles and a sensitivity analysis of how a widespread EV adoption will influence the market (Chapter 4).

To put these contributions in its context please refer to Table 1.1 from the introduction that shows the differences between the chapters.

5.1 Discussion

In the chapters of this dissertation we developed demand models on the city district level for (electric) vehicle rentals. These demand models serve as input for decisions to either reposition vehicles within a city, or develop pricing strategies to rent out idle storage from these vehicles on electricity markets. The decision mechanisms that we develop are based on GPS, transaction, time-series data, and weather conditions. We have demonstrated the accuracy of the decisions based on our models in several simulations and sensitivity analyses.

For the application of our models in electricity markets three target markets are relevant: the day-ahead, the intraday, and the operating reserve market. We have made two simplifications to make the analysis feasible within our resource constraints. First, we looked at these markets in isolation, even though fleet owners face an integrated decision making and can trade on all three markets consecutively. We study two of these markets because of their differing time till physical delivery. The day-ahead market with a relatively long time to physical delivery and the operating reserve market with a relatively short time to physical delivery. Therefore, we get an overview over both ends of the spectrum of time till physical delivery. As a consequence, the results we find are a lower, conservative bound of profits as fleets could potentially benefit even more when they are active in all three markets by arbitraging the highest and lowest prices from all three markets instead of only one market. The second simplification that we apply is that our decision mechanisms bid at a capacity price of zero in the operating reserve market. We do this to allow for an easier comparison to the intraday and day-ahead market. The consequence is that the profits we find are again a conservative estimate of the profits that a fleet owner would be able to make with a capacity fee. Despite these simplifications we find that applying our models is profitable for fleet owners.

Regardless of the simplifications related to an integrated decision making across all markets and capacity payments, we are confident that we have presented solid insights into the economic and societal implications of using the storage of electric vehicles for smart charging and vehicle-2-grid. We ground our confidence in the results in several sensitivity analyses that we have conducted in Chapter 3.6.4 Sensitivity Analysis: Charging Infrastructure, 3.6.5 Sensitivity Analysis: Price Changes, 3.6.6 Sensitivity Analysis: Scalability, Appendix 4.A. Sensitivity Analysis: Battery Size, Appendix 4.B. Sensitivity Analysis: Market Price, Appendix 4.C. The Effect of Large Scale Adoption on the Electricity Market. We find that smart charging and vehicle-2-grid increases annual gross profits of carsharing fleets by up to 4.2%, which are $164 for smart charging and $14 per vehicle compared to $3,900 from rental transactions. While these profits from smart charging and vehicle-to-grid are realistic in today's markets and price levels, they are economically not very significant. At first glance our findings would suggest, that the hype around electric vehicles as flexibility source for the smart grid is overrated. However, we think that this will be different in future electricity markets, which will value the flexibility of local storage from electric vehicles appropriately.

Currently, the grid is treated as a big copper plate where congestion is met with large infrastructure investments. There are some exceptions, where congestion at the transmission level is priced by Locational Marginal Pricing (LMP). This is appropriate for an energy landscape with large scale power plants that are connected to the transmission grid. However, as the energy generation transitions to decentralized energy sources that are connected at the distribution level, also the congestion on the distribution level needs to be addressed to guarantee a stable grid. This could either be solved by costly investments in the infrastructure and transformers in the distribution grid, or with markets that manage the grid congestion on the distribution grid. Research has already suggested market design changes to fit the requirements of distributed generation. Knaut and Paschmann (2017a,b) recommend to improve the market design of day-ahead and intraday markets by introducing a 15 minute day-ahead market to increase the coupling between the two markets. We think that these recommendations are very valuable, however, that they need to be complemented with regional markets that are able to price distribution grid congestion constraints. In such markets, the storage from electric vehicles would be an asset as it can be flexibly deployed throughout the whole city. The electric vehicles would be a valuable tool to balance the distribution grid and avoid costly infrastructure investments. Other balancing resources, such as power plants that currently deliver operating reserves or stationary storage, can only deliver electricity from their fixed location and therefore cannot always deliver what the market needs to meet the local congestion constraints. The large upside potential for electric vehicles in distribution grid markets would primarily be smart charging; vehicle-2-grid is still very costly due to the battery depreciation charges, even though this may change as prices for batteries drop. We encourage future research to design markets that support these local congestion issues and think that the option to balance the grid locally is critical, as it reduces the need for investments in distribution grid infrastructure.

The models that we develop in this dissertation are very suitable and adaptable to local electricity markets. In particular, the models developed in Chapter 2.3 Model, 3.4.1 Virtual Power Plant Decision Support: FleetPower, and 4.4 Methodology are able to predict the demand within a city at a high resolution. These models can distinguish between the availability of storage from electric vehicles per city district and price the storage accordingly. Several regulatory changes have to be made to the electricity markets in order for our models to unfold their full utility. However, with the ongoing trend towards distributed generation around the world we are confident that these changes will be pursued. These changes will make local smart charging from electric vehicles indispensable.

5.2 Summary of Main Findings and Implications

In this section we will briefly summarize the main findings of the individual chapters of this dissertation and their implications. In the following each Chapter will be discussed separately.

5.2.1 Main Findings Chapter 2

In Chapter 2 we show that predicting mobility demand for fleets by tracking vehicles locations and transactions is profitable for fleet owners. By partitioning space into hexagonal tiles, we allow for an equal distance to adjacent cells. This makes it easier to make recommendations about prepositioning vehicles. Our results indicate that fleets are currently significantly underutilized. With the prepositioning algorithm that we have presented in Chapter 2 fleets would be able to meet the demand with a smaller fleet. Important inputs to the model for predicting demand are historical rental transactions and points of interest. Weather data alone is not as strong of a predictor, even though it explains a part of the rental transactions given specific weather constellations. The results of this Chapter and the accuracy of the model to prepositioning vehicles is important for carsharing companies such as Car2Go or DriveNow, transportation network company such as Uber or Lyft, and autonomous vehicles in the future. Our results prove significant increases in profits for all three types of companies when taking relocation cost into account.

5.2.1.1 Limitations and Future Work Chapter 2

This research has two limitations that we leave open for future work. They are mainly related to the data that we could obtain. With more granular data future research will be able to address these issues with the same model we have introduced in this paper.

Instead of using daily weather data, hourly weather data may increase the accuracy of the model even further. For example rain is a strong predictor for rental demand. However, as the weather changes throughout the day this will also change the rental demand in the course of the day, i.e. there will only be elevated demand during the hours where it is actually raining. It would be interesting for future work, if they can find the granular historical weather data, to include hourly weather data in the model.

The transaction data of Car2go includes all transactions of rentals. However, this data does not provide information on demand in areas where there were no vehicles. We have partially addressed this issue of unobserved demand by serving the observed demand with a smaller fleet size. However, we currently collect data from Car2Gos competitor DriveNow about their rental transactions. Combined, the rental transactions from the carsharing services will give a more complete picture of the true underlying demand, based on which we will be able to confirm our model.

Repositioning is already profitable with fixed prices just by moving vehicles from low demand to high demand areas. Zonal pricing schemes would significantly enhance this concept and make even more relocations economical that were not economical with fixed prices yet. Our demand model is a very good basis to make recommendations for zonal pricing. We compute the expected value of a car parked in a certain zone at a certain hour. However, this is based on the current pricing model only. It is uncertain what would happen to the demand if prices were to change. Therefore, to make a good zonal based pricing model work future work needs to do a price sensitivity analysis. The best way to elicit this price sensitivity demand curve is through experiments where prices are changed.

There are dynamic effects of prepositioning on the the user base. If there is a better service due to prepositioning users may be more satisfied, will use the service more often, and it will attract more new users. Therefore, it may be a fruitful area for future research to investigate how better service effects the user base.

5.2.2 Main Findings Chapter 3

In Chapter 3 we show a machine learning based pricing strategy for electric vehicles. With this strategy fleets can participate in pay-as-bid secondary operating reserve auctions. We find that fleets can gain significant additional profits on top of their rental business to create value from idle electric vehicles. As the payoffs of renting vehicles are much higher than from selling storage on the secondary operating reserve markets we developed a model that takes the assymetric costs into account when deciding which and how many vehicles to sell storage from. The pricing strategy to bid on the auction includes information on opportunity cost that could be made by renting vehicles out instead of selling the storage, the battery depreciation cost, and cost of charging the vehicle in the first place (for vehicle-2-grid only). This flexible pricing model takes the varying likelihoods of rentals into account to determine the price. That way the fleet can be sure that the storage of vehicles will only be sold when the expected profits form a rental are exceeded. At current prices on the secondary operating reserve market, most profits from virtual power plants of electric vehicles come from savings related to charging the electric vehicles at times of excess energy, when buying energy is cheap. Current battery depreciation cost are too high to charge the vehicles when energy is cheap and resell it when it is more expensive, except for some rare events when the market prices peak suddenly. This happens, for example, when a transmission line is cut off or a power plant has to shut down for unplanned maintenance. However, we show that with the currently expected price decrease in batteries due to economics of scale vehicle-2-grid will also be more economical in the future. Currently the market in California and Germany are most suitable for virtual power plants due to the price volatility. The Netherlands have relatively low price differences due to the low renewable energy content in the electricity mix, making it less attractive for virtual power plants of EVs.

Additionally, we investigate in Chapter 3 how the placement of charging infrastructure at the most popular parking spot for Car2Go influences the business model of virtual power plants of electric vehicles. Results show that this is an important factor in cities such as San Diego, where there is insufficient infrastructure available, but is not a constraining factor for cities with well a developed charging infrastructure such as Amsterdam. The points where electric vehicles are parked most frequently but where there are no charging stations yet are also strategically very suitable locations to place charging infrastructure.

5.2.2.1 Limitations and Future Work Chapter 3

This Chapter has one limitation that is related to the market design of secondary operating reserves. The current market setup makes it very difficult for electric vehicles to participate. We formulated recommendations for changes to the market design in order to give equal access to conventional power plants and storage of electric vehicles to participate in the market. This is desirable because with increasing shares of renewables, conventional power plants will be phased out and their share in providing reliable back up power needs to be taken up by other resources such as electric vehicles. The capacity auction part (fixed component) should be done closer to the time of physical delivery, and participants should be able to bid for individual time slices of 15 minutes rather than in blocks of 8 hours as batteries cannot sustain delivering large amounts of energy for this long. Our model is a conservative estimation of the value of storage from electric vehicles in the future. Distributed generation and electric vehicle can cause local congestion. However, if managed according to the model introduced in this chapter electric vehicles can contribute to solving this issue when there is a local balancing market. We expect that the local value of storage will be significant. We consider future research in the value of the local aspect of storage to be very important.

5.2.3 Main Findings Chapter 4

In Chapter 4 we show an inventory allocation mechanism for electric vehicle fleets that recommends the optimal states for all electric vehicles in the fleet across charging (adding inventory), discharging for driving (decreasing inventory), discharging to the grid (decreasing inventory), or being idle (no change in inventory). Fleet owners make a trade-off between a class of demand where location matters (drivers want a car to be close to their place of departure) for a class of demand where location does not matter (vehicles can discharge to the grid from any capable charging point). With a mean weighted average (MAW) objective function we incorporate the asymmetric cost of charging, discharging, and renting.

Similar to Chapter 3 in the operating reserve market, we find in Chapter 4 that also in the double auction of the day-ahead market vehicles are used mostly for charging at cheaper hours to save on fuel cost and only infrequently for vehicle-2-grid.

Discharging vehicles via vehicle-2-grid is mostly unprofitable on the day-ahead market. The results from this chapter show that fleets can benefit from prices variances in the electricity markets and even have sufficient time to plan their charging transactions in advance.

When many electric vehicles and/or fleets participate in the energy market to benefit from cheaper electricity at certain times of the day and schedule the charging process accordingly this shifts the demand and supply curves. We find that the market urgently needs the flexibility from electric vehicles to charge whenever it is cheap, which has a positive impact on the triple bottom line. It decreases the electricity price for people, it reduces CO_2 emissions for the planet, and it increases profits for fleets. However, the profits diminish as more electric vehicle move to the cheaper timeslot.

Our MAW model with assymetiric payoffs is not only relevant to energy markets, but can also be transferred to other areas of research such as for example the caching literature. In caching it can be used to differentiate valuable content - for example commercials that earn more profits than other content.

5.2.3.1 Limitations and Future Work Chapter 4

Next to the value electric vehicles have to balance electricity demand and supply, electric vehicles are also well suited to play a role in distribution networks. Distribution networks have long term investment horizons (>40 years) but need to be adjusted to decentralized production. The proper market structures to give the right incentive structures to electric vehicles to act as a regional buffer in the distribution grid will be critical to a low cost distribution grid. Looking into the requirements of balancing markets on the distribution grid to deal with the challenges of distributed generation is a research area that is very relevant to the challenges of distributed generation in the electrical grid.

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Summary

The batteries of electric vehicles can be used as Virtual Power Plants to balance out frequency deviations in the electricity grid. Carsharing fleet owners have the options to charge an electric vehicle's battery, discharge an electric vehicle's battery, or keep an electric vehicle idle for potential rentals. Charging and discharging can be used to provide reliable operating reserves.

We develop an analytical model that manages carsharing fleets. On the one hand, the energy in the batteries of an electric vehicle can be made available to the grid as operating reserves. On the other hand, the electric vehicle can be made available for rental, where the location within the city matters: drivers want a car to be close to their place of departure or arrival. The model can also be used by Transportation Network Companies such as Uber to preposition their vehicles conveniently in a city or optimize zonal pricing.

To validate our model we develop a Discrete Event Simulation platform. We calibrate this simulation with locational information (GPS), rental, and charging transactions of 1,500 electric vehicles from the carsharing services Car2Go (Daimler) and DriveNow (BMW) over several years. We investigate the influence of the charging infrastructure density, battery technology, and rental demand for vehicles on the payoff for the carsharing operator and make an international comparison between the USA, Germany, the Netherlands, and Denmark. We show that Virtual Power Plants of electric vehicles create sustainable revenue streams for electric vehicle carsharing companies without compromising their rental business.

Nederlandse Samenvatting (Summary in Dutch)

Elektrische voertuigen (EV) kunnen potentieel worden gebruikt als virtuele energiecentrales ten behoeve van betrouwbare noodstroomvoeding. Autodeel-vlootbeheerders kunnen hun voertuigen laden, ontladen tijdens het verhuren, ontladen naar het elektriciteitsnet, of er niets mee doen om deze beschikbaar te houden voor potentiële klanten. We ontwikkelen analytische modellen met als unieke eigenschap dat deze beslissingen maken tussen enerzijds waar een EV beschikbaar wordt gemaakt voor de verhuur, waarvoor de locatie in een stad van belang is (bestuurders willen hun auto dicht bij de plaats van vertrek of aankomst hebben) en anderzijds het ontladen naar het elektriciteitsnet, waarvoor de locatie niet van belang is (EV kunnen via elke laadpaal die daartoe in staat is naar het net leveren). Deze modellen kunnen ook gebruikt worden voor Transportation Network Companies, zoals Uber, om hun voertuigen in een stad optimaal te positioneren of zonal pricing strategieën te optimaliseren. We ontwikkelen een Discrete Event Simulation en volgen de positie (GPS) en transacties van 1.500 EV van de autodeelserviceproviders Car2Go (Daimler) en DriveNow (BMW) over meerdere jaren. We onderzoeken de invloed van dichtheid van de laadinfrastructuur, batterijtechnologie en de vraag naar huurauto's op de winst van de autodeelbeheerder. Hiervoor maken we een vergelijking tussen de Verenigde Staten, Duitsland, Nederland en Denemarken. We laten zien dat virtuele energiecentrales van EV duurzame omzet voor autodeelvlootbeheerders creëert, zonder dat dit afdoet aan hun mogelijkheden om auto's te verhuren.

Deutsche Zusammenfassung (Summary in German)

Die Akkus von Elektrofahrzeugen können als Virtuelle Kraftwerke für zuverlässige Regelleistung zur Elektrizitätsnetzstabilisierung genutzt werden. Carsharinganbieter haben die Möglichkeit, Elektrofahrzeug-Akkus entweder aufzuladen, zu entladen oder die Fahrzeuge zur Vermietung bereitzuhalten. Auf- und Entladen der Akkus kann genutzt werden, um Regelleistung zu erbringen.

Es wird ein analytisches Modell zur Regelung von Carsharingflotten entwickelt. Zum einen kann die Energie des Akkus dem Netz zur Erbringung von Regelleistung zur Verfügung gestellt werden. Zum anderen kann das Auto für potentielle Vermietungen zur Verfügung gestellt werden, wobei der Standort eine wichtige Rolle spielt: Fahrer wollen möglichst Fahrzeuge benutzen, die sich in ihrer Nähe befinden. Dieses Modell kann auch von Online-Vermittlungsdiensten zur Personenbeförderung wie zum Beispiel Uber genutzt werden, um ihre Flotten innerhalb einer Stadt günstig zu positionieren oder Flächenzonentarife zu optimieren.

Zur Validierung des Modells wird eine Ereignisorientierte Simulations-Plattform entwickelt. Diese Simulation wird gestützt durch die Standortdaten, Vermietungs- und Ladetransaktionen von 1.500 Elektrofahrzeugen der Carsharingdienste Car2Go (Daimler) und DriveNow (BMW) über einen Zeitraum von mehreren Jahren. Dabei wird der Einfluss von Ladeinfrastrukturdichte, Akkutechnologie und Vermietungsnachfrage auf die Wirtschaftlichkeit für Carsharingflotten untersucht und ein internationaler Vergleich zwischen den USA, Deutschland, den Niederlanden und Dänemark gezogen. Es wird gezeigt, dass Virtuelle Kraftwerke aus den Akkus der Elektrofahrzeuge nachhaltige Einnahmequellen für Carsharingflotten schaffen, ohne das Vermietungsgeschäft zu gefährden.

About the Author

Micha Kahlen is an expert on the intersection of information technology, energy systems, and mobility. In his research he investigates economic aspects of virtual power plants that aggregate storage - of electric vehicles for example - to balance the grid.
Micha is a certified European Energy Exchange trader and won several awards: the second chapter of this dissertation was awarded a \$25.000 *Siebel Energy Institute Seed Grant* and the third chapter won the *European Energy Exchange (EEX) 2017 Excellence Award.*
Micha presented his work at top international conferences such as the Conference of the Association for the Advancement of Artificial Intelligence (AAAI), the International Conference on Autonomous Agents and Multiagent Systems (AAMAS), the European Conference on Information Systems (ECIS), and published in the journal *Applied Energy.*
Born on the 3^{rd} of December 1987, Micha grew up in Aachen, Germany, and volunteered in an institution for mentally disabled people in Israel after high school. Afterwards, he studied BSc International Business Administration (IBA) at the Erasmus University which we finished *cum laude* and where he participated in the *Erasmus Honours Programme.* He holds a MSc in Business Information Management, which he graduated *cum laude* with the highest GPA of 120 students in the core curriculum. After graduation, he worked as a consultant at Capgemini and did the project management of a €2 million data-warehouse project at the largest Dutch pension fund APG. Micha did his PhD in the Department of Technology and Operations Management at the Erasmus University. He taught his knowledge on software engineering to more than 300 Business Information Management master students as lead instructor for the course Designing Business Applications in 2015/2016 and in 2016/2017. His promoter is *Prof. Dr. W. Ketter* and his co-promoter is *Prof. Dr. A. Gupta* from the University of Minnesota. During his PhD Micha was also a visiting researcher at UC Berkeley.

Author's Portfolio

Publications

Journal Publications (Peer-Reviewed)

- Rieger, A., Thummert, R., Fridgen, G., Kahlen, M.T. & Ketter, W. (2016). Estimating the benefits of cooperation in a residential microgrid: A data-driven approach. *Applied Energy*, 180, 130-141 (Impact Factor: 5.746).

Professional Publications

- Kahlen, M.T. & Ketter W. (2015). Low Oil Prices - what effect will they have on Offshore Wind projects? *Offshore Wind*, 6(2), 42-44.

Papers Under Review

- Kahlen, M.T., Ketter, W. Dalen, van J. (2015). Electric Vehicle Virtual Power Plant Dilemma: Grid Balancing Versus Customer Mobility. (3^{rd} round).
- Kahlen, M.T., Ketter, W. & Gupta, A. (2016). FleetPower: Creating Virtual Power Plants in Sustainable Smart Electricity Markets. (1^{st} round).

Conference Proceeding Publications (peer-Reviewed)

- Kahlen, M.T., Ketter, W., Lee, T., Gupta, A. (2017). Optimal Prepositioning and Fleet Sizing to Maximize Profits for One-Way Transportation Companies. *38th International Conference on Information Systems (ICIS).* Seoul, South Korea (10-13 December 2017).
- Kahlen , M.T., Visser, S., Ketter, W., Lee, T. & Gupta, A. (2017). Geospatial Analytics: Predicting Cost-effective Charging Infrastructure Locations and

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Teaching

- Instructor for the Business Information Management Master course "Designing Business Applications" 2016/2017 (evaluation: 4.2/5) and 2015/2016 (evaluation: 4.1/5)

- Guest lecturer for the MBA course "Sustainable Smart Energy Business" 2014/2015

- Teaching assistant for the Business Information Management Master course "Designing Business Applications" 2014/2015 and 2013/2014

- Teaching assistant for the Business Information Management Master course "Next Generation Business Applications" 2014/2015 and 2013/2014

Master Thesis Supervision

Supervision of master theses (evaluation: 4.8/5)

- *'A contemporary examination on the effect of EV user behavior on range anxiety'* Nuno Genz 2014/2015

- *'A quantitative study on BEV and PHEV adoption in The Netherlands'* Brenda Janssen 2015/2016 [APPM]

- *'A study on the factors influencing the adoption of Hybrid and Electric Vehicles in The Netherlands'* Kristinka Wilmink 2014/2015 [Stedin]
- *'An Extensive Analysis and Evaluation of the Travel Patterns of Electric Vehicles'* Lisanne van Ooijen 2014/2015
- *'Assessing the benefits of coalition forming in residential energy generation'* Christian van Gelder 2015/2016
- *'Charging Ahead - Predicting Optimal Charging Station Locations across Multiple Cities'* Jonathan von Rüden 2016/2017
- *'Conquering Range Anxiety: How personal characteristics affect the adoption of electric vehicles.'* Romario Mohabiersing 2014/2015
- *'Designing Forecasting Algorithms for Charging Load Estimation: Pricing Policies for Energy Utilities'* Christina Papathanasi 2014/2015 [KPMG]
- *'Electric vehicle driving patterns in car-sharing services'* Omar Mayland 2015/2016
- *'Factors which Improve the Usage of Public Charging Points for Electric Vehicles'* Connie Lai 2015/2016 [Stedin]
- *'Incentives for off-peak charging of electric vehicles'* Rowan Siskens 2014/2015 [Stedin]
- *'Information Endowment in the Electricity Market; Capitalizing on Consumption Insights'* Niels van Langen 2015/2016
- *'Investing in Public EV Charging Infrastructure: Balancing Strategic Investments in Fast and Regular Charging Facilities across Different Levels of Urbanisation'* Glenn de Jong 2015/2016 [Stedin]
- *'Machine learning: From technology hype to business value'* Laurie Robben 2015/2016 [Accenture]
- *'Motivating flexible charging behavior of electric vehicles in office car parks'* Brent Bodenhorst Meyer 2014/2015 [Stedin]
- *'Personalization or privacy?'* Maxime van Egdom 2015/2016
- *'Risk and trust perception: Influences on the Willingness-To-Buy in Electronic Commerce in the Retail Industry'* Esther Hundepool 2014/2015 [PWC]

- *'The influence of master data management on data-driven sense making in a big data environment'* Charlotte van Laar 2015/2016 [KPMG]
- *'The Influence of Neighborhood Characteristics on Electric Vehicle Charging Locations for Peer-To-Peer Car Sharing'* Fangning Chen Chen 2016/2017
- *'The problem of electric long-chargers and its effect on effective public charging infrastructure utilisation: An analysis of charging transactions in an urban setting'* Nanne van der Wal 2016/2017 [City of Rotterdam]
- *'The value of points of interest information in predicting cost-effective charging infrastructure locations'* Stéphanie Visser 2015/2016
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- *'Valet Charging: Influence on Load Shifting, Charging Station Utilization and Prioritizing Queues'* Hidde van Heijst 2015/2016 [Stedin]
- *'What business model framework enables a manufacturer to effectively commercialize sustainable mobility products?'* Felix Brückner 2015/2016 [P3]

Certifications

- European Energy Exchange (EEX) Trader
- Cambridge English Certificate of Proficiency in English (Grade A)
- PRINCE2® Foundations
- University Teaching Qualification (UTQ)

Media

- RSM Discovery Video explaining the research from Chapter 3 (more than 1,500 views): `http://discovery.rsm.nl/articles/detail/199-turning-electric-vehicles-into-profitable-virtual-power-plants/`

Honors and Awards

- Siebel Energy Institute seed grant ($25,000)
- Erasmus Trustfonds Travel Grant for research visit to UC Berkeley (€1,300)
- European Energy Exchange (EEX) Excellence Award 2017 (€3,000)
- Winter Conference on Business Intelligence 2015 Most Commercial Impact Poster Award
- Autonomous Agents & Multiagent Systems 2014 Doctoral Student Scholarship ($500)
- Erasmus Honors Programme (2009)

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