POMS PRODUCTION AND OPERATIONS MANAGEMENT

PRODUCTION AND OPERATIONS MANAGEMENT POMS

Vol. 27, No. 11, November 2018, pp. 2054–2070
ISSN 1059-1478 | EISSN 1937-5956 | 18 | 2711 | 2054

DOI 10.1111/poms.12876

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

Micha T. Kahlen*
Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, Pennsylvania 3062, Rotterdam, The Netherlands,
kahlen@rsm.nl

Wolfgang Ketter
Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, Pennsylvania 3062, Rotterdam, The Netherlands
Faculty of Management, Economics, and Social Sciences, University of Cologne, Pohligstr. 1, 50969, Cologne, Germany,
ketter@wiso.uni-koeln.de

Jan van Dalen
Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, Pennsylvania 3062, Rotterdam, The Netherlands,
jdalen@rsm.nl

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, discharge for renting, discharge to the grid, or keep an EV idle. A unique property of our mixed rental-trading strategy is that 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 1500 real EVs on the "Nord Pool Spot," a North European electricity spot market. A Fourier series approach captures the demand patterns of carsharing vehicles accurately, especially when our weighted objective function with asymmetric payoffs is applied. We show that the VPP can be profitable to fleet owners, ecologically advantageous through reductions in wind power curtailment, and beneficial to consumers by reducing energy expenses.

Key words: electric vehicles; energy informatics; smart electricity markets; sustainability; virtual power plant; smart charging
History: Received: April 2015; Accepted: February 2018 by Subodha Kumar, after 3 revisions.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) stated that human-induced climate change causes eight systematic environmental hazards. Among these 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, CO_2 emissions need to be reduced. 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, 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 back-up to ensure that electricity is available when needed. This approach is not only 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 virtual power plants (VPP).

As EVs are more widely adopted, storage capacity for electricity becomes increasingly available. This capacity may be employed to offer balancing services to the grid (Sioshansi 2012, Vytelingum et al. 2011), but this depends on the trade-off between the operating costs, such as battery wear, and potential profits. In this research, we consider the electricity stored in EV batteries as inventory. The battery can be allocated to four, mutually exclusive states: charge (add inventory), discharge for renting (decrease inventory), discharge to the grid (decrease inventory), or left idle (no change in inventory). While the optimal allocation of EVs over time can be considered a multi-period inventory flow problem, day-ahead EV 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 car sharing fleet. In the basic flow, where a private person owns a single EV, inventory can be substituted. The owner can decide between charging, discharging, driving, and leaving idle. When considering fleets of EVs, the location matters, as rental 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) and a class of demand where location does not matter (vehicles can discharge to the grid from any capable charging point in a city).

We develop a mixed rental-trading strategy to analyze the potential for EV fleet owners to gain profits from renting out cars, while at the same time using spare battery capacity and excess electricity to actively trade in the energy market. This fleet of EVs is considered as a VPP, a collection of distributed energy sources, which 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 VPPs, which act on fluctuating electricity price signals. Our strategy optimizes electricity purchases of EV fleet owners in the market to charge the fleet for the purpose of driving, or discharge at a later stage at a price premium. The proposed strategy is validated with real energy market data and real data about electric vehicles, whose movements we track with GSM (Global System for Mobile Communications) and GPS (Global Positioning System). This technology provides us real-time information about 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 exogenous (Sioshansi 2012) or that battery storage is static (Vytelingum et al. 2011). When driving patterns are regarded as exogenous, this dispenses with any uncertainty over when EVs will be available to store electricity. By contrast, our strategy applies to uncertain environments, where rental trips are not known in advance. Moreover, we take into account the corresponding costs of immobility of customers for the fleet owner. Concerning the electricity market, we use individual bidding preferences from a real-world electricity auction to infer about the current and future behavior of market participants using large-scale data. Using individual asks and bids, we replicate the market clearing mechanism including the bids and asks of trading fleet owners. The advantage of this approach is that we can add additional bids and asks to this market to analyze how the market prices change, if fleet owners place bids and asks or if competition increases. If there is increased charging by EVs, the demand curve shifts; if there is increased EVs discharging, the supply curve shifts, all in accordance with market auction 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 the CO_2 emissions.

We validate the proposed strategy using real-life data from the Nord Pool Spot electricity market in Northern Europe and a fleet of 1100 EVs from Daimlers carsharing fleet Car2Go in San Diego, Amsterdam, and Stuttgart, as well as a fleet of 400 EVs from BMW's carsharing company 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 the car is returned anywhere within the city boundaries. An incentive scheme of ten free driving minutes encourages customers to park at charging stations to recharge the EVs, when the state of charge is below 20%. In our analysis, 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 analysis addresses the challenges of the current and future energy landscape in terms of the triple bottom line, considering the impact for people, planet, and profit (UN 1992). Our contribution is to help embedding sustainable renewable energy sources in energy systems and add to the existing knowledge 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%, decreases the need to curtail renewable energy sources by 97% (planet), and offers profit increases of 4.3% for fleet owners (profit).

The study is structured as follows. First, we review related literature and the theoretical background of energy markets (section 2), and then proceed to describe the mixed rental-trading strategy for EV fleet owners (section 3). Next, we go in detail about the data used and the methods applied (section 4). The analysis and the impact of our strategy on people, planet, and profit are described in section 5. We present a summary and conclusion of our research combined with an outlook on future work in section 6.

2. Theoretical Background

This section describes relevant research and explains the general setting of balancing renewable energy sources with EV fleets. In particular, we will describe the research that has been done on charging EV fleets with variable prices to save cost. Consequently, we position our research within the literature on EVs and the vehicle-2-grid context of selling electricity back to the grid. Next, we introduce the methodological background and make a comparison with the related topic of caching. Finally, we describe the functioning of the electricity wholesale market.

2.1. Smart Charging of Electric Vehicles

The additional demand from charging EVs does not pose serious problems to the generation capacity of the grid in the long term (Sioshansi 2012), as grid capacity can be increased gradually in the system. However, the introduction of 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 the 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 to understand the implications of charging for 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. 2014, Wolfson et al. 2011). Other studies recommend that users 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.

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 electricity 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), 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 (http://www.edison-net.dk/). Vytelingum et al. (2011) investigated the effects of using static storage capacity for a household to store energy when it is cheap. They showed that a 14% saving in the energy bill could be achieved, with carbon emissions being reduced by 7%. Other studies demonstrated that the yearly benefits of V2G are in the range of 20 to 120 US$ (Peterson et al. 2010) and 135 to 151 US$ (Reichert 2010), acknowledging that battery cost are a crucial factor for the realized profitability. Based on a price sensitivity analysis, Reichert (2010) show that batteries are seldom used for V2G when battery degradation costs are 50 US$/MWh, whereas they can be profitably used at degradation cost of 10 US$/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) and Kahlen et al. (2017) extend this finding by showing that charging costs can be decreased with more than 7% when trading on ancillary service markets, and that V2G activities therefore become profitable for fleet owners. However, these studies consider the operating reserve market, where the commitment to deliver electricity has to be made a week in advance. In the day-ahead market, which is the focus of the present study, these commitments are only made twelve hours in advance. This allows one to make much more accurate demand forecasts, which significantly reduces the risk of not being able to serve rental customers. Also, since we focus on the day-ahead market, which is much more important in terms of the quantity traded, we are able to assess economic implications.

Relatively little research has been conducted into the impact of uncertainty of rental demand as a result of not knowing in advance when EVs are needed for driving at which location. In contrast to previous work, our approach can be applied even when rental demand is not known in advance.

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 (e.g., Kleindorfer et al. 2005); and the automobile industry is no exception. The past decade has seen the emergence of new business models, like car sharing, aimed at increasing vehicle utilization. The present study sets out to demonstrate how electric vehicle fleet owners can exploit EVs to their full potential by using excess storage for energy trading. This potential can be achieved by allocating storage efficiently to 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 develop a strategy that is informed by research in the caching literature, which has addressed a similar storage problem. Caching refers to the storage of data in order to improve web browsing performance, so that frequently accessed information is locally available and does not need to be downloaded again. 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 in anticipation of future demand is similar to our EV storage problem, which is why we follow a similar approach of estimating demand, developing a mixed rental-trading strategy, and consequently empirically testing the strategy. A parallel to the fleet dimension of our research can be drawn with collaborative caching, in which items are cached in multiple locations, for example, other computers in an organization (Datta et al. 2003). This is relevant to our study, as storage is shared among several users (similar to carsharing), 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. Location is important for our problem, which previously has been modeled as an inhomogeneous Poisson process in (Datta et al. 2003). But in addition, time is crucial for our mixed rental-trading strategy, 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 (Bichler et al. 2010, Gallien and Wein 2005, McCabe et al. 1991). 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.

2.4. Day-Ahead Electricity Wholesale Market Mechanism

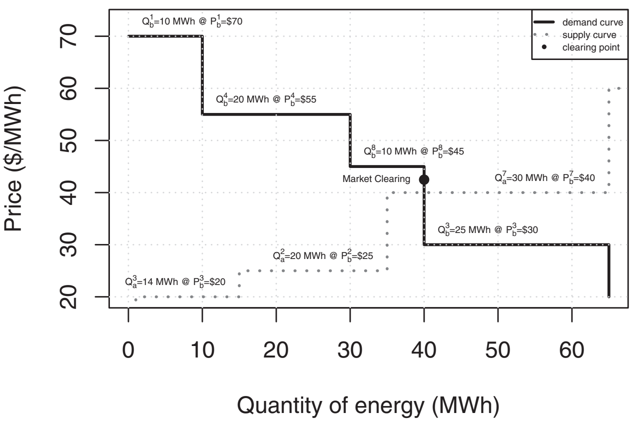
Fleet owners normally charge their EVs with a flat electricity tariff negotiated with an electricity provider. However, if they want to benefit from energy price differences over time, they have to become active in the wholesale market. A particular consequence of this energy market presence is that fleet owners have to determine the quantities of electricity that they are willing to store and sell back to the grid, the minimum price at which they would like to sell electricity and the maximum price at which they would be willing to buy the stated amount of electricity, for each time slot one day-ahead. These quantities and prices are matched with those of other buyers and sellers in the day-ahead electricity wholesale market. In this section, we explain the operation of the energy market before we go in detail on our mixed rental-trading strategy.

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 $P^j_{S,t}$ they are willing to accept, for time slot t. Buyers k place 'bids' that state the quantity $Q^k_{D,t}$ they want to buy and indicate the maximum price $P^k_{D,t}$ they are willing to pay for a specified time slot t.

Production and Operations Management 27(11), pp. 2054–2070, © 2018 The Authors. *Production and Operations Management* published by Wiley Periodicals, Inc. on behalf of Production and Operations Management Society

Figure 1 Illustration of the Wholesale Market Clearing Mechanism for a Particular Time Slot



The fleet owners assume the role of suppliers when they discharge the EVs, and the role of buyers when they charge EVs. After the orders are submitted, the market operator arranges all bids and asks in merit order: the cheapest asks and the bids with the greatest willingness to pay are prioritized, as illustrated in Figure 1. The asks in the merit order make up the supply curve for electricity, while the bids in merit order form the demand curve for electricity. The intersection of both curves defines the equilibrium clearing price P_t^* that equalizes supply and demand. In Figure 1 the clearing price P_t^* is equal to 41.5 US\$, which is the same for all executed bids (1, 4, and 8) and asks (3, 2, and partially 7). The clearing quantity Q_t^* defined as the sum of executed order quantities, is equal to 20 MWh. All (partial) orders to the right of the market clearing solution are either asks that sell at a price that no consumer is willing to pay, or bids by consumers that no seller is willing to accept, and are thus rejected.

3. A Mixed Rental-Trading Strategy

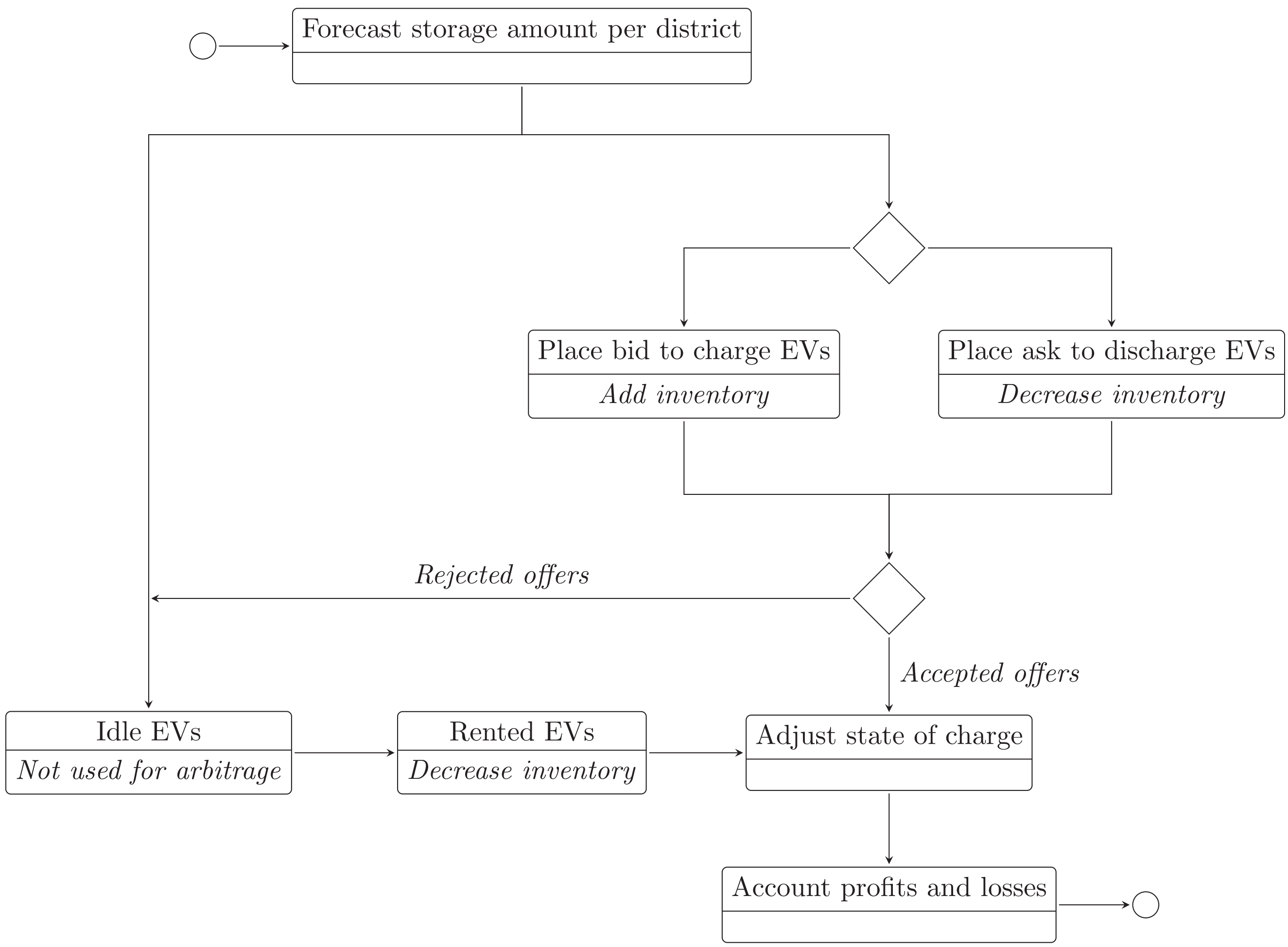
Our study takes the perspective of EV fleet owners who operate VPPs by exploiting the collective battery capacity of their EVs for rental and energy trading. These fleet owners are simultaneously active in the (carsharing) rental market and the energy wholesale market, and routinely have to decide about the desired state of their vehicles for different time slots one day-ahead: charging (adding inventory), discharging to the grid (decreasing inventory), or leaving idle (not changing inventory), of which the latter may or may not lead to discharging for car rental (decreasing inventory). The energy stored in EV batteries can be used to meet peak demand in electricity consumption, while available battery capacity can be made available to store energy in times of excess supply. Fleet owners who engage in buying or selling electricity for arbitrage purposes, will be cautious not to turn away rental customers, which would jeopardize the much more profitable rental transactions. 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 slot due to, for instance, too low remaining battery after discharging. As the intended transactions on the wholesale market need to be submitted twelve to thirty-six hours in advance, the allocation of EVs to the different states is based on forecasts of battery availability for all time slots on the next day.

In addition, rental patterns can be expected to differ between different parts of cities, which are the natural rental domains of fleet owners. As it is expensive to relocate vehicles, which requires staff and resources, the availability of vehicles for arbitrage will be different between city districts. Fleet owners can exploit these geographical differences by using vehicles at less popular rental locations and time slots for arbitrage. Our proposed mixed rental-trading strategy considers these location-dependent vehicle allocation decisions, while assuming that demand within city districts is relatively homogeneous, as people are willing to walk short distances.

The day-ahead electricity market closes at noon for the next day, implying that the bids and asks with the respective reservation prices and quantities to charge and discharge have to be submitted between twelve and thirty-six hours in advance for all twenty-four hourly time slots of the next day. Carsharing customers, by contrast, typically decide spontaneously whether or not to rent a car: cars are booked maximally half an hour in advance. As a consequence, fleet owners have little deterministic information available about future energy and rental conditions.

Figure 2 illustrates the proposed mixed rental-trading strategy for fleet owners. It reflects the various actions, decisions, and consequences of car (sharing) rental and trading in the energy wholesale market for fleet owners acting as VPPs, on a daily basis. Each day before noon, fleet owners forecast the number of EVs and the energy storage potential that is available for trading, for each time slot and city district, one day-ahead. Based on these forecasts, EV battery capacity is considered for arbitrage, if no rental is expected, or left idle, otherwise. Next, the fleet owner decides about the asks and bids to submit, based on the aggregate state of charging and the available capacity for charging across all city districts. After the market auctioneer has determined the clearing prices and quantities, fleet owners engage in using the available EVs for energy charging or discharging, if the bids or asks are excepted, or add these EVs to the rental stock, if the bids or asks are not accepted. After each time slot, when the precise usage of EVs have

Figure 2 Mixed Rental-Trading Strategy for EV Fleet Owners Acting as VPPs



materialized, that is, rental, trade, or left idle, the associated financial transactions are used to update the fleet owner's account. Below, we elaborate the various stages of the mixed rental-trading strategy. Table 1 summarizes notation for convenience.

3.1. Determining the Quantities to Charge and to Discharge

Every day, the fleet owner has to decide about the quantities to charge or discharge for all time slots of the next day. As the rental market is uncertain, the fleet owner's decisions are based on forecasts of the rental demand, and of the state of charge of EVs per location and time slot. Though detailed location information is provided by the GSM and GPS of the EVs in real time, 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 this 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 per city district and time slot. Moreover, location is critical for rental, but is irrelevant to energy trading. It is not important for the grid from where EVs deliver the actual physical electricity as a service to the electricity markets, as long as the asks and bids that are accepted by the market are honored by some EVs from the fleet. Decentralized markets that may exist in the future could even benefit from the distributed nature of carsharing vehicles throughout a city, which would increase the business case for our mixed rental-trading strategy even more.

The total amounts of energy that a fleet owner can charge from the grid ($Q_{D,t}$) or discharge to the grid ($Q_{S,t}$) during time slot t are obtained by aggregating the EVs' excess storage or electricity over the locations in a city. Specifically, the total amount of energy, $Q_{D,t}$, that batteries can be charged with, that is, the bid quantity for charging, is defined as the total storage capacity of EVs in excess of the electricity needed for rentals aggregated over all districts l:

$$Q_{D,t} = \sum_{l=1}^{L} q_{D,t,l}/(1 - e_c) \qquad (1)$$

Table 1 Table of Notation

Symbol	Explanation
α_l	Location-dependent period of the rental cycle pattern
β_l	Amplitude of the rental cycle pattern
b	Battery depreciation costs per kWh of a charging-discharging cycle
e_c	Efficiency rate during charging and conversion
e_d	Efficiency rate during discharging
i, I	Specific electric vehicle (EV), $i = 1, \ldots, I$
l, L	District within a city (location), $l = 1, \ldots, L$
$m_{l,t}$	Miles rented in district l at time t
P^*_t	Market clearing energy price for time slot t
P^k_D	Price of a bid (demand) from buyer $k = 1, \ldots, K$
P^j_S	Price of an ask (supply) from supplier $j = 1, \ldots, J$
$\bar{P}_R$	Price of an average rental trip in a city
$q_{D,l,t}$	Storage available at location l during time slot t in excess of the storage needed for rentals
$q_{S,l,t}$	Electricity stored at location l during time slot t in excess of the electricity needed for rentals
$Q_{D,t}$	Potential to store quantities of electricity in the EVs during time slot t; quantity of a bid (demand)
$Q_{S,t}$	Potential electricity quantity to sell in the EVs during time slot t; quantity of an ask (supply)
$r_{t,i}$	Amount of energy used for rentals of EV i in time slot t
$SoC_{t,i}$	State of charge of EV i at the beginning of time slot t
$SoC_{\max,i}$	Maximum state of charge capacity of EV i
$SoC_{\min,i}$	Minimum state of charge capacity of EV i
t, T	Hourly time slots for delivering energy, $t = 1, \ldots, T$
u, U	Days of the estimation window, $u = 1, \ldots, U$
π_m	Marginal profit per mile rented

where e_c is the efficiency rate for charging, which captures the energy losses when converting from alternating current to direct current, and $q_{D,t,l}$ is the available storage in excess of the storage needed for rentals at location l during time slot t. Similarly, the total amount of energy available for discharging, $Q_{S,t}$, the ask quantity for discharging, is the aggregate of the EVs' available electricity in excess of the electricity needed for rentals over all city districts l:

$$Q_{S,t} = \sum_{l=1}^{L} q_{S,t,l}(1 - e_d) \tag{2}$$

with $q_{S,t,l}$, the total electricity stored at location l in excess of the electricity needed for rentals; and e_d, the efficiency rate for discharging.

The determination of the excess amounts of storage ($q_{D,t}$) or electricity ($q_{S,t}$) takes into account the technical constraints of EV batteries and the driving needs of renters. EVs can only be used for trading energy, if they are connected to charging stations. Cars that are rented out, or parked at locations without charging facilities are not available for arbitrage. Moreover, as car rental is always preferred over trading, the state of charge of EVs at the end of time slot t, $SoC_{t+1,i}$, should always be enough to sustain the energy consumption needed for driving during the next time slot, $r_{t+1,i}$, which implies:

$$SoC_{t+1,i} \geq r_{t+1,i} \tag{3}$$

The storage capacity available for arbitrage ($q_{D,t,l}$) is equal to the difference between an EV's maximal state of charge, $SoC_{\max,i}$, and its state of charge at the beginning of a time slot t, $SoC_{t,i}$, aggregated over all connected EVs in district l. The energy available for discharging ($q_{S,t,l}$) should respect the fleet owner's priority in Equation (3), and consists of the difference of the state of charge at the start of a time slot minus the energy needed for rental, aggregated over all connected EVs in location l. The contribution of an individual EV i to the discharging amount in time slot t is thus equal to $\max(0, SoC_{t,i} - r_{t+1,i})$.

3.2. Determining the Bid Price to Charge and the Ask Price to Discharge

The fleet owner submits offers to the energy market to charge (bids) and discharge (asks) for every time slot one day ahead. These offers contain both a quantity and a reservation price. As pricing needs to be scalable to make inferences for multiple fleets, we develop a pricing strategy that can be computed efficiently. This strategy is based on two thresholds, which are determined during a training period. If the market price exceeds the first threshold, the fleet owner should sell electricity (issue asks), while if the price falls below the second threshold, the fleet owner should buy electricity (issue bids). This is implemented as a limit order market (Handa and Schwartz 1996).

For the bid price, we assume that the fleet owner specifies a maximum price at which to buy for a particular time slot, $P_{D,t}$, equal to the average market clearing price for a particular time slot, $\bar{P}^*_{t|U}$, observed over the preceding time period:

$$\bar{P}^*_{t|U} = \frac{1}{U}\sum_{u=1}^{U} P^*_{t-uT} \tag{4}$$

where U is the length of the preceding period in days, and T is the number of time slots per day. In this way, the fleet owner's bids are only matched if the market clearing price is at or below the average clearing prices observed during the training period.

For the ask price, we specify the minimum price at which the fleet owner would be willing to sell energy for a particular time slot, $P_{S,t}$, as the average clearing price for this time slot during a training period, $\bar{P}^*_{t|U}$, with an adjustment for the battery deprecation cost per kWh discharged, b: $P_{S,t} = \bar{P}^*_{t|U} + b$. This 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.

The market may or may not accept the fleet owner's offer depending on the composition of the offer as well as on the offers of other market participants. Once the offers are out, the market auction mechanism ultimately decides when EV's will charge or discharge. If offers are rejected, the excess storage or surplus of energy will be added to the stock of idle EVs, which are available for rental services. If offers are accepted, the states of charge of the electric vehicles will accordingly be adjusted.

3.3. The Fleet Owner's Account

The fleet owner generates revenues by allocating vehicles to the states of charge, discharge, leaving idle or rental. Trade-offs are made between buying and selling electricity from and 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, then this will reduce the rental profits, and vice versa. After the decision about the day-ahead fleet allocation is made, the auction mechanism has determined the day-ahead clearing prices, and the car rental of the next day has materialized, the fleet owner's daily profits follow as:

$$\Pi = \sum_{t=1}^{T} \left\{ Q_{S,t}(P_t^* - b) - Q_{D,t}P_t^* + \sum_{l=1}^{L} m_{l,t}\pi_m \right\} \quad (5)$$

where T is the number of day-ahead time slots 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 during time slot t, and π_m is the marginal profit per mile rented.

4. Data and Methods

4.1. Data

Real-life data about vehicle rental and energy market trading are used to evaluate the viability of our mixed rental-trading strategy. This section describes the various sources and the nature of the EV rental data, the energy market data, and the characteristics of battery costs and conversion losses.

Rental data. We use data about EV fleets in four cities: Amsterdam, with seven districts; Copenhagen, with eleven districts; San Diego, with seven districts; and Suttgart, with eleven districts.

EV usage data is available from Daimler's EV carsharing service Car2Go (www.car2go.com) in San Diego (300 EVs), Amsterdam (300 EVs), and Stuttgart (500 EVs), and from BMW's carsharing service DriveNow (www.drive-now.com) in Copenhagen (400 EVs). The data from Copenhagen are particularly relevant to our analysis, as they come from the only city which is part of the Nord Pool Spot market. Under the carsharing services from Car2Go and DriveNow, customers rent 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, thus highlighting the similarity of the two services.

The Car2Go and DriveNow data include the following information about idle cars: (i) current time, which is used to determine the time slot t; (ii) vehicle ID; (iii) GPS coordinates, which are used to define location l; and (iv) state of charge (SoC), whether it is parked at a charging station, and whether it is currently charging. All data are available on the web in real-time for all 1500 EVs. Daimler AG gave permission to access a private API to harvest these data every five minutes for research purposes. For DriveNow, we used a self-built web scraper to download EV data every five minutes. Table 2 gives a snapshot of the data. The EV data are complemented with data about charging station locations. Access to information about the charging state of each car and the location of charging stations enables us to calculate how much electricity each EV can store, and how much electricity it can sell from each location.

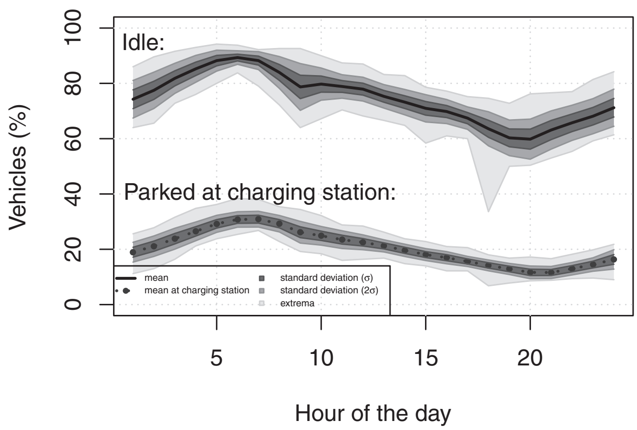
Data for Stuttgart were collected from November 2013 till December 2014, and for San Diego and Amsterdam from March 2014 till December 2014. Data between March 31st and April 20th 2014 are lacking due to a server error of our web scraper. The data for Copenhagen was collected later, from August till December 2016 in order to validate our findings with a city within the Nord Pool Spot region. Since DriveNow has a relatively new user base (it started operating in 2015 in Copenhagen, while Car2Go started four years earlier) some of the usage patterns may not be comparable, and therefore need to be interpreted with caution. However, we use a rolling time horizon for the forecasting, which will quickly pick up changing behavioral patterns over time. The size of our estimation window is sixty days.

Table 2 Sample EV Data

Time t	ID i	Address	SoC	Charging spot	Charging
May 13, 2014 19:25:00	S-GO2059	Sommerrainstraße 90, 70374 Stuttgart	96	TRUE	FALSE
May 13, 2014 19:30:00	S-GO2059	Sommerrainstraße 90, 70374 Stuttgart	96	TRUE	FALSE
May 13, 2014 20:30:00	S-GO2059	Im Buchwald 19, 70186 Stuttgart	85	FALSE	FALSE

Note. 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.

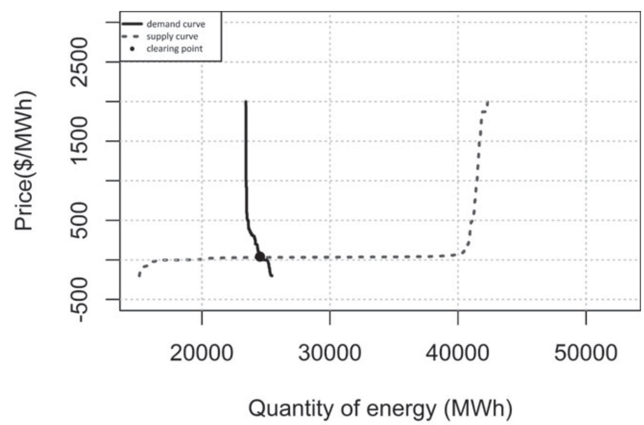
Figure 3 Average Driving Patterns with Standard Deviation for Car2Go's Carsharing Fleet, Stuttgart



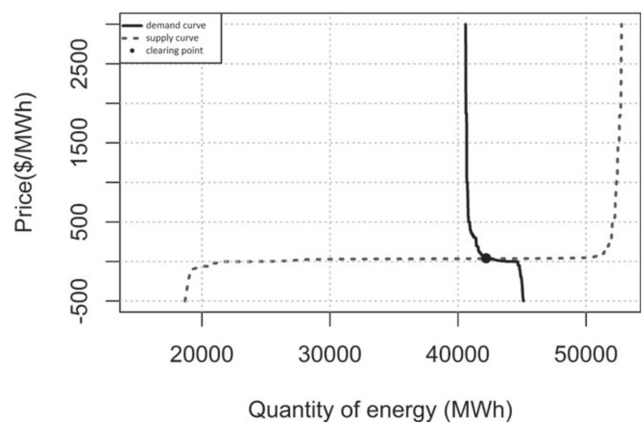
All EVs are subcompact cars. The EVs from Car2Go are Smart Fortwo electric drives with a 16.5 kWh battery ($SoC_{\max}$). The EVs from DriveNow are BMW i3 with an 18.8 kWh battery ($SoC_{\max}$). All EVs within a particular city thus have the same maximum state of charge. Online Appendix S1 gives a sensitivity analysis for battery size. Figure 3 shows the percentage of idle EVs over the course of a day for Stuttgart. As may be expected, fewer EVs are idle during the day than during the night. This pattern is especially pronounced during the afternoon and evening rush hours, when on average 60% of EVs are idle. A rental peak can be observed during the morning rush hour at 9 AM, but this peak is small compared to the peaks in the afternoon and evening. Apparently, carsharing is used more frequently after work, and not as much for commuting or during office hours. The lowest observed idleness of EVs over the whole period is 34%, which occurs in the afternoon rush hour. During the night hours, almost all EVs are idle. At its extreme, 94% of the cars were not used, which creates room for arbitrage. Figure 3 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, which percentage seems stable over the day. Only EVs parked at a charging station can be used to provide storage to the energy market. As the number of charging stations can be expected to increase over time, the trading profits that we find are likely to be a conservative estimate.

Using real data about electric vehicle fleets worldwide and about day-ahead electricity markets, we are able to validate our mixed rental-trading strategy in a representative setting. An objection might be, however, that we evaluate the profitability of EV fleets from San Diego, Amsterdam, and Stuttgart with the day-ahead electricity market data from a different region, that is, Denmark. The results for these cities need to be interpreted with care, but still we are confident that our findings are representative for these regions as well.

Figure 4 Demand and Supply Curves Consisting of Individual Asks and Bids in the Nord Pool Spot Market, Complemented with Additional Bids from EV Fleet Owners



(a) July 15th, 2013, 0-1 AM



(b) December 1st, 2013, 5-6 PM

Energy market data. Detailed order information was kindly made available by the Northern European Nord Pool Spot (ELSPOT) electricity market (www.nordpoolspot.com), a day-ahead market for the Scandinavian and Baltic region which populates about 360 buyers and sellers who trade on average over 40,000 MWh of electricity per hour—a fleet of 500 EVs can store approximately 0.02% of this amount. The data consist of about eight million individual bids and asks over the 365 days of the year 2013. Each hourly time slot includes more than 2000 asks or bids. Based on these data, we reconstruct the trading settlements for all 8760 (=365 days × 24 hours) clearing events, following the mechanism described in section 4. Figure 4 shows the demand and supply functions for two exemplary clearing events, for July 15, 0–1 AM, and December 1, 5–6 PM.

In the case of Figure 4, the supply curve is based on 582 asks from sellers whose asks looked like: $Q_S^1 =$ 15,114.01 MWh, ..., $Q_S^{582} =$ 42,304.32 MWh, with corresponding ask prices $P_S^1 = -200$US$/MWh, ..., P_S^{582} = 2000US$/MWh. The demand curve similarly consisted of 314 bids from interested buyers. The market clearing price for this time slot amounted to 39US$/MWh at which 24,550 MWh are sold. In a similar manner, the time slot in Figure 4b involved 704 asks and 396 bids, leading to a market clearing price equal to 41US$/MWh, trading 42,200 MWh.

The Nord Pool Spot market is particularly suited for this analysis, because it is the largest energy market in the world, but also because it has a large share of renewable energy sources in the electricity mix. The latter makes it representative of future energy markets, as more and more energy from renewable source will come available.

Using detailed data about actual bids and asks in the market allows us to study the impact of the market entrance of EV fleet owners acting as VPPs. Moreover, it allows us to mimic the effect on market clearance of additional orders by the fleet owner, and thus evaluate the consequences of scaling the mixed rental-trading strategy. The use of empirical bid and ask data is preferred over formal modeling of the stochastic processes involved, because the decision making of market participants will change when they re-evaluate their options and when they are confronted with new choices, such as the storage opportunities provided by EVs (Shen and Su 2007).

Battery costs and conversion losses. As the developments in battery technology are essential to determine profitability (Schill 2011), yet difficult to predict, we consider three battery scenarios. The first scenario assumes that battery cost are zero, $b = 0$, and is meant as a benchmark. The second scenario assumes that capital cost decrease to 70 US$/kWh, while the number of cycles increases to 7000, with a resulting battery depreciation cost of $b =$ 10US$/MWh. The third scenario is based on the current battery price of approximately 150 US$/kWh capital costs depreciated over 3000 life cycles.[1] 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 are $b =$ 50US$/MWh. Whenever a fleet owner trades, the wear-out depreciation costs of the battery capacity used needs to be taken into account for that transaction. Furthermore, about 3% to 4% of the energy is lost due to the conversion efficiency (e_c) when the EV is 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.

Limitations of the data. With the data from both real electric vehicle fleets around the world and real day-ahead market data we are able to substantiate our claims in a representative setting. However, we evaluate the profitability of EV fleets from San Diego, Amsterdam, and Stuttgart with the day-ahead electricity market data from Denmark. Because of this geographic discrepancy the results for these cities need to be interpreted with care. Nevertheless, we are confident that our findings are also representative for these regions for two reasons. First, the analysis of the DriveNow data from Copenhagen, which matches the day-ahead market data from Denmark geographically, shows similarly positive results to the other cities. Second, the day-ahead markets in the respective cities operate according to the same double auction principle and have comparable market clearing prices. For detailed information please refer to Appendix S2. Sensitivity Analysis: Market Price.

4.2. Methods

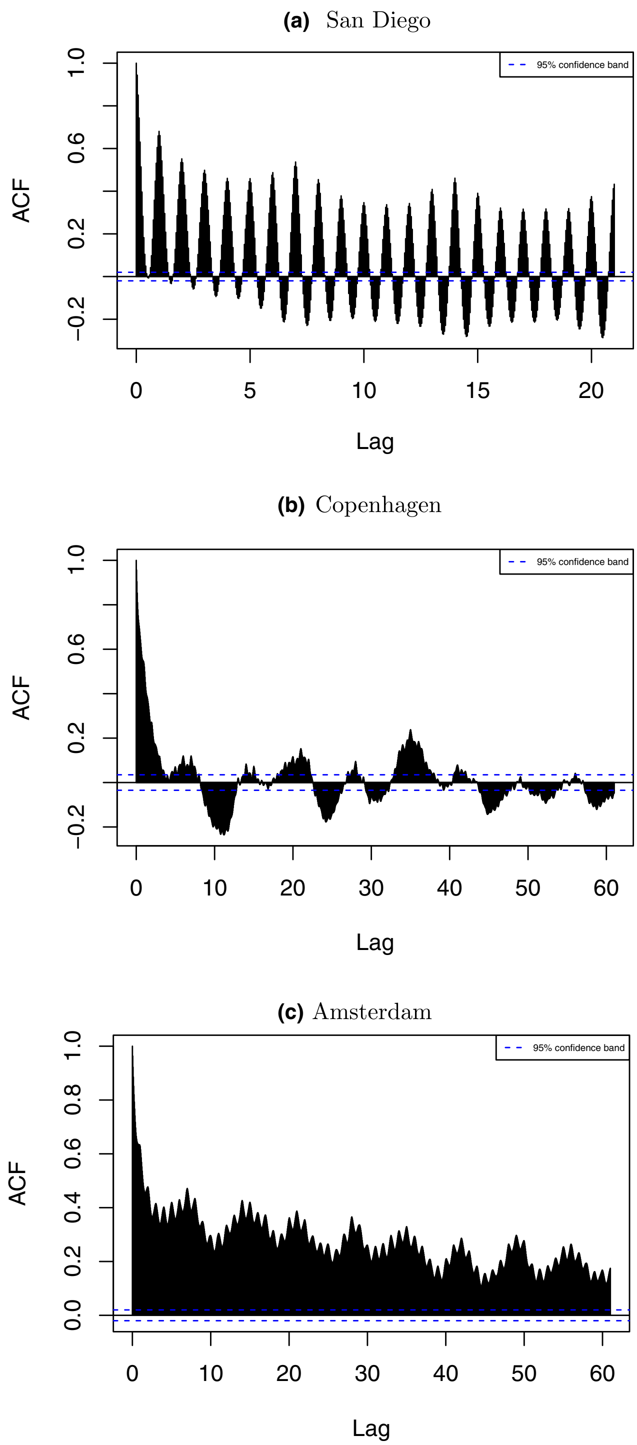
The amounts of energy to charge and discharge in each day-ahead time slot, $q_{D,t}$ and $q_{S,t}$, are forecasted by means of a bottom up approach: first, the amounts of energy to charge or discharge for each location l and time slot t, $q_{D,t,l}$ and $q_{S,t,l}$, are forecasted, after which aggregate day-ahead forecasts are obtained by summing over the locations.

The hourly excess storage amounts exhibit strong cyclical patterns over time, which is illustrated by Figure 5, showing the autocorrelation functions of excess storage for selected districts in the three cities of interest. These patterns suggest alternating sequences of excess storage and excess electricity, which differ between the three cities. While some districts, such as Down Town San Diego, exhibit daily recurring patterns as in Figure 5a, other districts, such as Indre By in Copenhagen exhibit weekly patterns as in Figure 5b. Yet other districts reveal a combination of weekly and daily patterns, such as Nieuw-West in Amsterdam, see Figure 5c.

We adopt a Fourier series approach to forecast these complex seasonal patterns of excess storage and excess energy for each district. The available storage for charging vehicles at location l and time slot t is represented by the following:

$$q_{D,l,t} = \sum_{k=1}^{7} \{\beta_{D,l} \times \sin(2\pi \times k \times t_l/\alpha_{D,l}) + \beta_{D,l} \times \cos(2\pi \times k \times t_l/\alpha_{D,l})\} \quad (6)$$

Figure 5 Autocorrelation Functions of the Storage Availability in Different Cities [Color figure can be viewed at wileyonlinelibrary.com]



where $\beta_{D,l}$ defines the amplitude of the repeating rental pattern in district l and $\alpha_{D,l}$ defines the periods of the repeating rental pattern in district l. The available storage for discharging vehicles at location l and time slot t is modeled as follows:

$$q_{S,l,t} = \sum_{k=1}^{7} \{\beta_{S,l} \times \sin(2\pi \times k \times t_l/\alpha_{S,l}) + \beta_{S,l} \times \cos(2\pi \times k \times t_l/\alpha_{S,l})\} \tag{7}$$

where $\beta_{S,l}$ defines the amplitude of the repeating rental pattern in district l and $\alpha_{S,l}$ defines the periods of the cyclical excess energy pattern in district l. Seven Fourier terms are used to capture potentially various forms of seasonality. Single parameters $\alpha_{D,l}$ and $\alpha_{S,l}$ are assumed per region, in order to conveniently handle the computational consequences of simulating the impact of EV fleets with different sizes.

In addition, we adopt an asymmetric weighted loss function to estimate models (6) and (7), which weights positive and negative forecast errors differently. Ordinary objective functions, such as the minimization of the sum of squared forecast errors, are less suitable in view of the asymmetric pay-offs (Amaldoss and Jain 2002, Christoffersen and Diebold 1996, 1997, Elliott et al. 2005, Granger 1999, Granger and Pesaran 2000, Zellner 1986). Not being able to rent out cars is much more expensive for the fleet owner (the average price in a city $\bar{P}_R$ a rental customer pays for a drive is 15 US$) than the cost of selling electricity on the energy market P^*_t. The asymmetric weighted objective function penalizes forecasts according to the costs in each direction. Under-forecasting excess storage is heavily penalized, as this storage could jeopardize the much more profitable rental services, while over-forecasting the excess storage is much less penalized, as the associated payoff is low compared to rental profits. The objective function for the two models is defined as:

$$\min_{\alpha_l,\beta_l} \sum_{t=1}^{N} w_{t,l}|q_{t,l} - \hat{q}_{t,l}| \tag{8}$$

$$\text{with } w_{t,l} = \begin{cases} P^*_t & \text{if } q_{t,l} - \hat{q}_{t,l} \geq 0 \\ \frac{|q_{t,l}-\hat{q}_{t,l}|}{SoC_{\max,l}} \bar{P}_R + P^*_t & \text{if } q_{t,l} - \hat{q}_{t,l} < 0 \end{cases} \tag{9}$$

in order to avoid repetition, $q_{t,l}$ refers to $q_{D,t,l}$ or $q_{S,t,l}$ depending on whether the excess storage (6) or the excess energy (7) functions are estimated. Likewise, α_l refers to $\alpha_{D,l}$ or $\alpha_{S,l}$ and β_l refers to $\beta_{D,l}$ or $\beta_{S,l}$; N is the total number of time slots used in the optimization, and $SoC_{\max,l}$ is the aggregate of the maximum state of charge of EVs in a city district l.

5. Analysis: The Triple Bottom Line

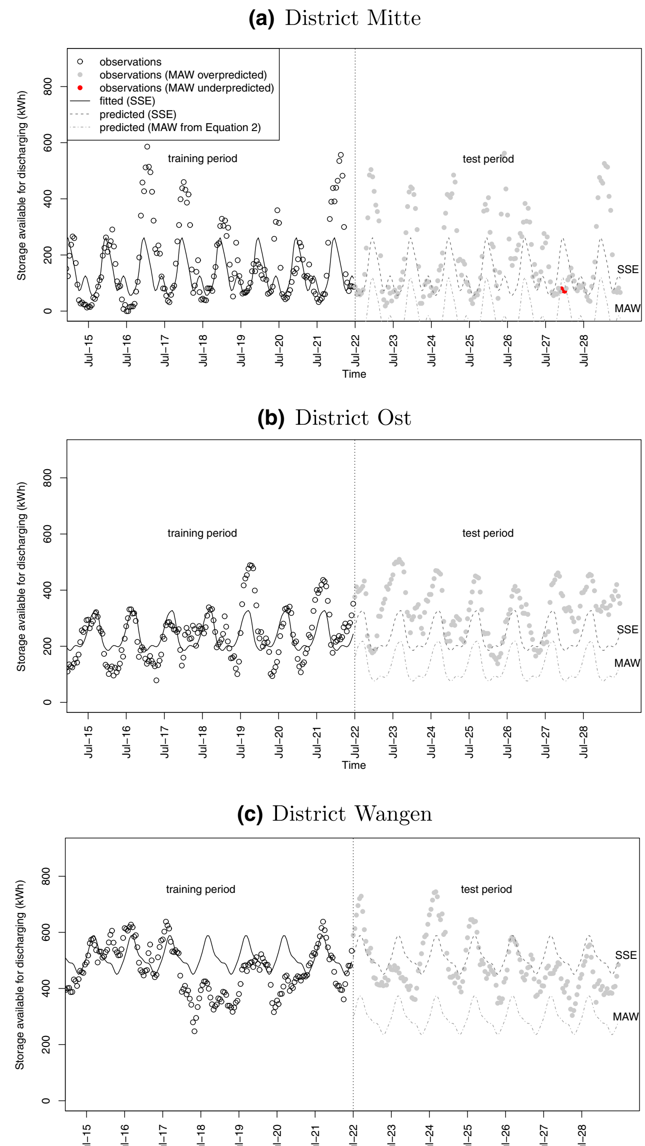
In this section, we analyze the results of our simulation with the mixed rental-trading strategy for EV fleet owners. We evaluate the effects of VPPs that consist of EVs in terms of the triple bottom line. First, we evaluate the effect of mixed rental and energy trading on the financial viability under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

5.1. 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 this allocation affects the profits of the fleet owner and the risk he faces of not being able to serve his core business, the rental to customers. We analyze the profits of the allocation, and how the profit is influenced by fleet size and competition.

5.1.1. Allocation to States: Charging, Discharging (Rentals), Discharging (Grid), Idle. We find that the allocation of our mixed rental-trading strategy is profitable for fleet owners with a very low risk of reducing the service level for rental customers. Our strategy allocates a fleet's 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 owners profits. This allocation is based on forecasts of the electricity available for discharging and storage for charging during the previous sixty days per location. Figure 6 gives an example of the rolling window forecast of the available excess energy for discharging for three districts, Mitte, Ost, and Wangen, in Stuttgart. The figures show the observed available excess energy for trading in individual time slots, a fitted model based on the minimization of the sum of squared forecast errors (SSE), and the holdout sample predictions: one based on the same SSE model, and one based on the minimization of asymmetric weighted forecast errors (8). Given the high cost of missing a rental compared to the cost of not being able to trade, the model based on (8) yields more conservative forecasts of the electricity available for discharging. In fact, only for one day during the holdout period in Figure 6, on the noon of July 26, 2016, for one district, Stuttgart Mitte, this model under-predicts (as marked in Figure 6a), where more EVs should have been reserved for rentals than indicated by the forecast. Note that the opposite, that is, over-prediction, where the model indicates that less storage is available than there actually was, happens frequently (as marked in Figures 6a–c). However,

Figure 6 Forecasts of the Excess Energy Available for Discharging for the Districts Mitte, Ost, and Wangen in Stuttgart [Color figure can be viewed at wileyonlinelibrary.com]



this type of decision error is not as costly and fleet owners lose out on only a few cents, while at the same time the chance that one of these EVs cannot be rented out, is decreased.

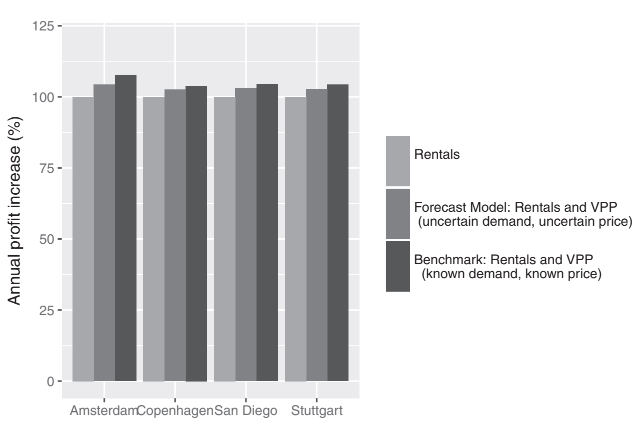
The observed daily excess storage patterns differ between the districts. For example, Figure 6a for Stuttgart Mitte reveals that relatively much storage is available for discharging during noon, while Figure 6b for Stuttgart Ost and Figure 6c for Wangen show that more storage for discharging is available during the night. The available storage variability, though, is larger in Ost than in Wangen. These differences between districts are advantageous for the trading decisions of the fleet owner, as the aggregate storage available for trading is distributed more or less evenly over the day.

The number of EVs that is to be allocated to the charging state is determined with the asymmetric weighted objective function (8) in the same way as for discharging. The other two states, leaving idle and discharge for renting, are the EVs that remain. These EVs are idle until a customer decides to rent them. In the next section, we consider how the allocation decision pays off for the fleet operator financially.

5.1.2. Benchmarking. For the four cities considered, Figure 7 shows the fleet owner's annual profits under three conditions: (i) exclusively rentals under a flat electricity tariff; (ii) a mixed rental-trading strategy with uncertain day-ahead rental demand and electricity prices; and (iii) a mixed rental-trading strategy with perfect information about day-ahead rental demand and electricity prices. The latter outcome serves as a benchmark to indicate how much annual profit the fleet owner could have achieved, if rental transactions and energy prices had been perfectly known in advance. If EV fleet owners, like Car2Go or DriveNow, offer their EVs without the pre-booking option, then they may come close to the benchmark profits. But they will never reach this outcome because of the uncertainty in the rental and energy markets.

In the four cities, EV fleet owners make more profits when applying the mixed rental-trading strategy than only renting out their EVs. The mixed rental-trading strategy with VPPs consistently outperforms the rental-only strategy and comes close to the benchmark assuming perfect information. Across cities, we see an annual profit increase per vehicle of between 173 US$ and 252 US$ depending on the city (2.5% and 4.3%) compared to the benchmark with perfect information where between 262 US$ and 447 US$ (3.9% and 7.7%) are theoretically possible per EV. In the next section we show how the annual profit is influenced by fleet size and competitive effects.

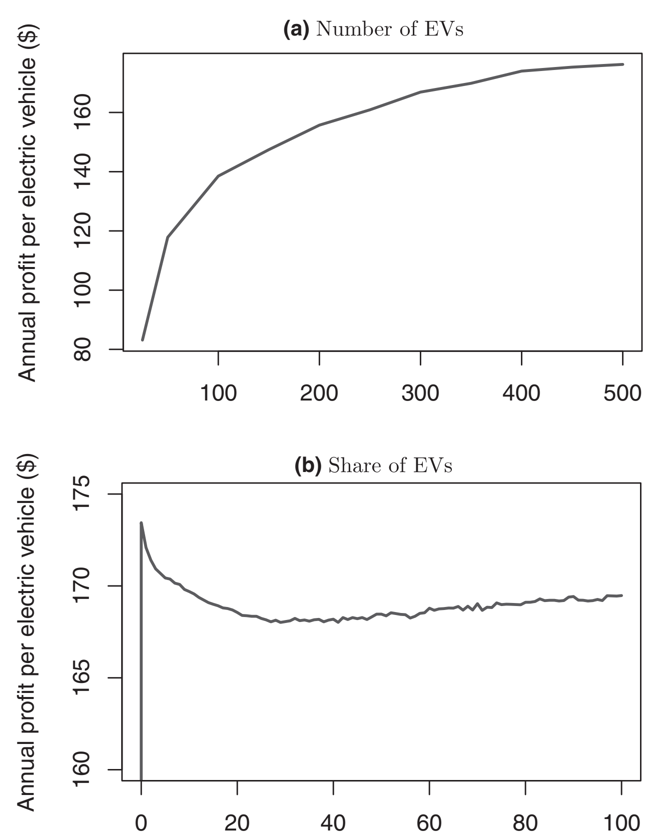
Figure 7 **Profit Comparisons of the Different Strategies for EV Fleets in Amsterdam, Copenhagen, San Diego, and Stuttgart**



5.1.3. Fleet Size and Competitive Effects. Forecasting the excess storage or electricity available for trading, as a basis for the fleet owner's allocation decisions, is facilitated by the size of the fleet. As fleet size increases, it becomes easier for fleet owners to forecast at which locations idle EVs can be reserved for charging or discharging.

Figure 8a shows the profits per EV as a function of fleet size, for Copenhagen. It shows that annual profit per EV increases steeply for fleet sizes between 25 and 100 vehicles and then gradually levels off for larger fleet sizes. The monotonously increasing pattern suggests that it is best for fleet owners to have a fleet, which is as large as possible for VPP purposes. Competition has the opposite effect, however. The more EV fleets compete as VPPs on the energy market, leaving all other bids and asks as is, the more the arbitrage opportunities between low and high prices are reduced. Figure 8b shows how trading profits vary with the share of EVs relative to rental vehicles with internal combustion engines. Note that we do not assume a change in total demand because if demand increases, also the supply will increase in the long run canceling each others effect out on average (Sioshansi 2012). Therefore, we focus on the effect of our mixed

Figure 8 **Annual Profits as a Function of the Number (a) and share (b) of Electric Vehicles (example of Copenhagen)**



rental-trading strategy on the market equilibrium over the course of the hours of a day.

We assume perfect competition among fleet owners on the electricity market due to more than 2000 market participants, where we simulate the situation where several independent fleet owners of 500 EVs each participate in the electricity market as VPP.

These independent fleet owners submit bids and asks to the market. Equilibrium prices are determined by the supply and demand from many actors. No single participant can set the prices for electricity. As a group, however, these fleet owners do have an effect on the market. As illustrated in Figure 8b, the market yields diminishing returns for every additional EV that enters the market until the EV market share reaches about 20%. Fleet owners make relatively high profits when the share of EVs in the market is low (<20%). Under these circumstances, each fleet owner annually makes between 173 US$ and 168 US$ per EV, of which between 20 US$ and 23 US$ 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 market price difference for arbitrage decreases. This effect rewards early adopters with premium returns. When the market share of EVs is above 20% virtually all additional profits for fleet owners come from charging EVs at a cheaper than average rate. These findings are consistent with Peterson et al. (2010) and Reichert (2010), who found profits of 20–120 US$ and 135–151 US$ respectively, but for a low market share of EVs. This is an important contribution because, unlike previous research, we do take into account the uncertainty about when EVs are likely to be used, and yet we demonstrate that this type of mixed rental-trading strategy can be profitable.

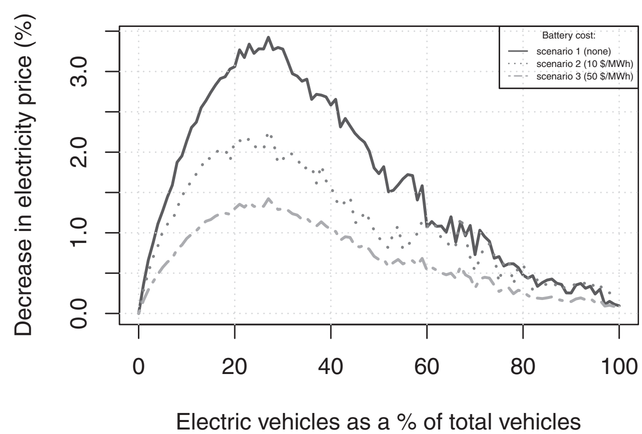
5.1.4. Battery Cost Effects. Battery depreciation costs appear to have a marginal impact on the profitability of the mixed rental-trading strategy. The total profits for a fleet owner in the first scenario with no battery depreciation cost are only 9% higher than those in the third scenario with battery costs equal to 50 US$/MWh. This somewhat surprising outcome may be explained by the fact that the majority of orders are high-volume trades with low profit margins, and thus represent only a small share of the total annual trading profits. Most of the trading profits are generated from a few asks that involve small quantities, but have extremely high arbitrage margins, so that battery depreciation costs are of relatively little importance. We therefore find that battery depreciation plays a limited role for our strategy, which may be different for other strategies, like the one considered by Reichert (2010). Different outcomes may also be due to energy market differences, but in view of the increasing share of renewable energy sources worldwide, the Nord Pool Spot market is considered a relatively attractive information source. See Online Appendix S2 for a sensitivity analysis of the market price.

5.2. People: Societal Perspective

In contrast to the diminishing returns under competition for fleet owners, there are increasing benefits for 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 energy supply increases while demand remains the same, which lowers the clearing price. However, when fleet owners charge their EVs for use as VPPs, the demand increases while supply remains the same, adversely affecting the clearing price for consumers. Both affect the overall system cost in a positive way. Figure 9 shows the electricity price reduction for electricity consumers in a society as a function of the EV market share. The figure suggests that the 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%, and the wholesale electricity price is reduced by 1.5% to 3.4%. This price reduction is somewhat less when battery depreciation costs are higher and competition increases, because under these conditions fewer trading orders are made. The price reductions are significant for all three battery depreciation scenarios at the 1% significance level,

Figure 9 **Electricity Price Reduction as a Function of EV Penetration in Denmark**



based on a two sample t-test with unequal variances. By contrast, previous research found a 14% reduction in energy prices (Vytelingum et al. 2011), which however does not consider the trade-off between driving and balancing the grid.

5.3. Planet: Carbon Emissions

EVs have 10% to 25% lower global warming potential than combustion engine vehicles when accounting for all life-cycle emissions (Hawkins et al. 2013). This includes the additional emissions arising during the battery production, which are on average 15% of an EVs life-cycle emissions (Notter et al. 2010). In our study, we seek to isolate the effect emission reductions caused by VPPs. We do not consider emission reductions from fuel efficiency of EVs and potential emission increases from producing vehicle parts and batteries (combustion engine vehicles vs. electric vehicles). The latter effects can then be included by other studies with a broader scale. Our mixed rental-trading strategy reduces CO_2 emissions, as we will now explain in detail.

For each hourly time slot 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, which means that, for example, wind turbines that have enough wind to produce electricity, need to be shut down. Our mixed rental-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 when the demand exceeds the renewable energy production. This has a positive effect on the total CO_2 reduction of the energy system.

To assess the CO_2 reduction potential of our mixed rental-trading strategy, we measure the quantity of energy that did not need to be curtailed and instead replaces 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 during each time slot t; the total demand for electricity in this time slot; the amount of energy that was charged to the electric vehicles during the time slot; and the amount of energy that was discharged from the batteries to the grid during time slot 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 study, 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.

6. Conclusion 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. We have presented a strategy, which is both profitable for electric vehicle fleet owners and sustainable for society and planet. The proposed mixed rental-trading strategy allows fleet owners to charge their electric vehicles more cheaply, use their storage capacity for arbitrage trading, and rent out these vehicles as usual. Our mixed rental-trading strategy 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) and a class of demand where location does not matter (vehicles can discharge to the grid from any capable charging point). We have developed an objective function with asymmetric losses, which considers the asymmetric cost of renting, charging, and discharging at different city districts in Amsterdam, Copenhagen, San Diego, and Stuttgart. The mixed rental-trading strategy is well suited to predict demand with unique characteristics across different districts of a city. We show that our mixed rental-trading strategy enhances the profits of electric vehicle fleet owners significantly; they can earn between 173 US$ and 252 US$ (2.5%–4.3%) more profits annually per electric vehicle under the current Nord Pool Spot market prices. These profit ranges are similar to those mentioned by Peterson et al. (2010) and Schill (2011). But, by contrast, our results take into account the uncertainties of EV rental demand and the variable prices on the day-ahead market. While we demonstrated the usefulness of our arbitrage strategy in the carsharing setting, it can also be extended to the caching literature. In particular, our forecast model with asymmetric payoffs could prove useful in differentiating valuable content for example commercials that earn more profits than other content.

We applied large-scale analytics to 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%. We have also presented evidence that our mixed rental-trading strategy reduces CO_2 emissions, because 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 significant profits with this strategy. Though, profit levels will decrease when more vehicle fleet owners compete on this market. In our current approach we focus on idle electric vehicles. 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. The study of incentive structures and mechanisms of electric vehicle storage in micro grids is another promising field of application for VPP 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.

Acknowledgments

We thank Konstantina Valogianni for her feedback, support, and advice in the early stages of this manuscript.

Note

[1]www.forbes.com/sites/samabuelsamid/2015/10/28/lg-chem-may-be-on-the-verge-of-dominating-ev-battery-industry/#52d4d003144d (accessed date February 10, 2016) and www.saftbatteries.com/force_download/li_ion_battery_life__TechnicalSheet_en_0514_Protected.pdf (accessed date February 10, 2016).

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Supporting Information

Additional supporting information may be found online in the supporting information tab for this article:

Appendix S1: Sensitivity Analysis: Battery Size.
Appendix S2: Sensitivity Analysis: Market Price.