Aggregating Electric Cars to Sustainable Virtual Power Plants: The Value of Flexibility in Future Electricity Markets

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Abstract

Electric vehicles will play a crucial role in balancing the future electrical grid, which is complicated by many intermittent renewable energy. We developed an algorithm that determines for a fleet of electric vehicles, which EV at what price and location to commit to the operating reserve market to either absorb excess capacity or provide electricity during shortages (vehicle-2-grid). The algorithm takes the value of immobility into account by using carsharing fees as a reference point. A virtual power plant autonomously replaces cars that are committed to the operating reserves and are then rented out, with other idle cars to pool the risks of uncertainty. We validate our model with data from a free float carsharing fleet of 500 electric vehicles. An analysis of expected future developments (2015, 2018, and 2022) in operating reserve demand and battery costs yields that the gross profits for a carsharing operator increase between 7-12% with a negligible decrease in car availability (<0.01%).

Introduction

In its World Energy Investment Outlook 2014, the International Energy Agency estimates that over the next 20 years a cumulative investment of $53 trillion is required worldwide to limit the concentration of greenhouse gases in the atmosphere to 450 parts per million of CO_2 (International Energy Agency 2014). First concrete steps in that direction require European Union member states to have a 30% renewable content by 2030; especially intermittent wind and solar power is subsidized (The European Parliament and The Council of the European Union 2009). These large scale penetrations of volatile renewable energy sources pose a challenge to the stability of the electrical grid as their production is inflexible to changing demand and difficult to forecast (Kassakian and Schmalensee 2011). This complicates balancing the grid and providing sufficient energy to consumers at all times, thereby increasing the chance of blackouts.

Smart grids offer an information based solution that utilizes the transition from data poverty to data richness in the electricity sector. According to Malhotra, Melville, and Watson this also paves the way for real-time control of energy use for many devices. Important in that regard are electric vehicles (EV) which have storage capacities that can contribute to solving the imbalance problem. The EVs are charged when wind and solar sources produce energy, and they make energy available to the grid when those energy sources are unavailable, called vehicle-to-grid (V2G). Together they constitute a *virtual power plant* (VPP), which are distributed power sources that are centrally coordinated to support flexible energy supply. Specifically we look at very short term (seconds to minutes) integration of demand and supply on the operating reserve market. We combine real-time information from electric cars about their location, usage, and battery storage, with information from reserve markets in an algorithm to optimally allocate EV capacity. This algorithm, which we call *FleetPower*, makes an explicit trade-off between benefits from offering cars for rental and using them for balancing the grid in real-time which was not considered in previous research (Vytelingum et al. 2011; Voice et al. 2011). To the best of our knowledge this is the first study that uses real driving, charging, and locational data of 500 EV in 54 urban districts. The data for this study was provided by the Daimler AG.

Background and Literature

This section describes and explains relevant research and the general setting of balancing renewable energy sources. First the embedment in the trading agent literature in a sustainability context will be given. Consequently, we will describe the operating reserve market in more detail from where the VPP sources its revenues. Finally, we will position our research within the literature on EVs and the carsharing context.

Agent-based Sustainable Society

Previous research employed intelligent trading agents to act on behalf of consumers in decentralized electricity markets. A prominent example is the Power Trading Agent Competition (Power TAC) where brokers compete to attract customers and purchase electricity on their behalf (Ketter, Collins, and Reddy 2013). The realism of the platform was demonstrated by Ketter, Peters, and Collins. Similarly to other brokers such as defined by Urieli and Stone and

Reddy and Veloso we outline a broker that acts on behalf of carsharing fleets only and focuses on the operating reserve market. We take advantage of particulary high electricity prices on the operating reserve market that stem from real-time changes in electricity demand and production. In a similar vein to Ketter et al. who make real-time pricing decisions based on economic regimes, we make real-time decisions for renting out a specific EV or turning it into a VPP. Another example of the benefits of agents in decentralized electricity markets is illustrated by Ramchurn et al..

Operating Reserves: Balancing the Electrical Grid

If at any point in time there is a difference in the quantity of electricity produced and consumed, the electricity market has to be regulated in real-time to maintain stability. This is coordinated by electronic auctions, specifically first-price sealed-bid auctions, in which participants make *offers* to generate electricity, called positive operating reserves, or *bids* to absorb and consume electricity, called negative operating reserves. The balancing responsible party accesses these offers and bids as needed in the merit order (cheapest resources are used first) to keep the market in an equilibrium. This mechanism gains importance with increasing levels of intermittent renewable energy, as production depends on exogenous factors such as the weather. Especially battery storage is valuable in this regard because it has no ramp-up costs and time. Ramp-up costs and time to start-up generators are significant for base load power plants. EVs possess large electrical batteries that are almost instantly scalable. Previous research proposed to use this capacity to offer balancing services to the grid (Vytelingum et al. 2011; Peterson, Whitacre, and Apt 2010; Schill 2011).

Electric Vehicles and Carsharing

Carsharing and especially the free float carsharing model, where the car can be picked up and dropped off anywhere, contribute to more sustainable ways of transport in terms of construction, operation, and decomposition of mobility systems. Firnkorn and Müller find that even under a pessimistic scenario, free float carsharing has a significantly positive effect on carbon emissions.

Charging many EVs in the same neighborhood at the same time will overload transformers and substations quickly (Kim et al. 2012; Sioshansi 2012). Previous research has addressed this issue by proposing smart charging. Smart charging means to charge EVs at times when the grid is less congested to complement peaks in electricity consumption. Drivers are incentivized to shift their charging, yielding significant peak reductions (Valogianni et al. 2014). An extension of smart charging is the V2G concept which was mentioned in the introduction. Regarding the technical feasibility it should be noted the standard of the International Electronical Commission ICE 62196 supports V2G. A study by Vytelingum et al. looked at the savings a household can make with a battery exposed to variable pricing at the energy wholesale market and found that efficient use of the battery would save 14% in utility costs and 7% in carbon emissions. Other studies find yearly benefits per EV of \$ 10-120 (Peterson, Whitacre, and Apt 2010) and \$ 176-203 (Schill 2011). Within this research stream there are two conflicting opinions regarding the economic feasibility of the V2G concept. Peterson, Whitacre, and Apt contend that relatively low yearly benefits per EV would not justify a widespread roll out. Kahlen, Ketter, and van Dalen, however, argued that V2G would enable volatile renewable energy sources to be suitable for mainstream usage. Tomic and Kempton show that the profitability depends on the target market; the larger the variations in the electricity price the higher the profitability.

Previous research greatly contributed to this topic, however under the unrealistic assumption that driving patterns are known in advance. So they consider a static system, whereas in reality it is a complex sociotechnical system (Geels 2004). Users have valuations for being mobile that differ over time and conflict with market interests (Vytelingum et al. 2011; Tomic and Kempton 2007). We approach this problem from a sociotechnical perspective by appropriating valuations for mobility from price and demand for the EVs in a carsharing context. Besides, in contrast to our work, previous studies have used either very small fleets or data from combustion engine vehicles which have a longer range and are not subject to range anxiety, the fear of stranding with an empty battery.

Model Description

At the core of this research is the development of an algorithm that decides how to deploy EVs, and its evaluation in a simulation environment. A simulation approach is most suitable for this purpose as we are dealing with a complex system that would be prohibitively expensive to build. It would be difficult to manipulate a variety of parameters to find the optimal market equilibrium. A simulation approach helps to refine the algorithm, which is driven by business needs from its environment that was discussed in the introduction, and applying knowledge from existing agent-based approaches.

Virtual Power Plant Decision Support: FleetPower

The algorithm, which we call FleetPower, decides which EVs should be deployed as part of a VPP, which EVs should be charged, and which EVs should be made available for rental for one time interval ahead in real-time. This applies only to EVs that are parked at a charging spot for the time under consideration.

Individual Car Performance Indicators. FleetPower calculates the expected profit performance indicator (PPI) for a specific EV i over time interval t (see Equation 1). Therefore it maximizes expected profits over renting (rental benefit RB), charging (negative regulation benefit NRB), and turning the car into a VPP (positive regulation benefit PRB).

$$PPI_{t,i,l} = \max(RB_{t,i,l}, NRB_{t,i,l}, PRB_{t,i,l}) \tag{1}$$

For a table of notation including measurement units see Table 1. The expected profits for renting (RB) car i during interval t parked at location l is estimated with a multiple linear regression model (see Equation 2). The regression is based on the probability with which a car gets rented out (a)

and the storage capacity available (q). The probability to be rented out at a given location varies over every quarter of an hour and differs for each day of the week. As rental benefits are generally much higher than benefits from PRB and NRB a car that was predicted not to be rented out when it actually was rented out will be much costlier than the other way around. To account for these asymmetric misclassification costs, we use the upper confidence interval as predictor for RB. The level of confidence depends on the magnitude of the asymmetric misclassification costs. During rentals the battery is used and depreciation costs (D) as well as electricity costs for charging (C) for the expected difference in the battery state before and after driving (ΔQ) are taken into account.

$$RB_{t,i,l} = \beta_1 + \beta_2 a_{t,l} + \beta_3 q_{t,i} - \left[D + \left(\frac{C}{\epsilon}\right)\right] \Delta Q_{t,i} \quad (2)$$

where:

$$\Delta Q_{t,i} = \beta_4 + \beta_5 a_{t,l} + \beta_6 q_{t,i} \quad (3)$$

If an EV is parked at a charging station FleetPower has the option to charge the car. In this respect the negative regulation benefit (NRB) is defined as the quantity with which the battery of car i at interval t can still be charged with (Ψ) and the bid price for negative operating reserves (P^{neg}), which differs per EV i and time interval t (see Equation 4). More specifically the quantity that the battery can still be charged with (Ψ^{neg}) in time interval t takes into account the amount of electricity stored in the battery Q and the charging speed γ, which is defined by $\Psi^{neg}_{t,i} = \min((\Omega_i - Q_{t,i}), \gamma\Delta t)$. As this option would replace the costs for charging, we add the opportunity benefit of not having to pay for charging fees (C). In other words the NRB is the difference between what one would pay with a common electricity tariff and the negative operating reserve market price.

$$NRB_{t,i} = \Psi^{neg}_{t,i}(P^{neg}_{t,i} - C) \quad (4)$$

The bidding price is determined by the cost that would be incurred to charge the EV with the regular electricity tariff C and charging inefficiency ϵ, the expected rental profits RB, and profit margin μ^{neg} which maximizes overall profits for the time intervals t in the test data set (see Equation 5). Note that if P^{neg} is too high, the market will instead choose a cheaper bid and consequently there is no NRB for that time period.

$$P^{neg}_{t,i} = -\frac{C}{\epsilon} + RB_{t,i,l} + \mu^{neg}_t \quad (5)$$

In a similar vein an EV could also contribute to a VPP. The electricity stored (Ψ^{pos}) in EV i that can be accessed within time interval t and the offered selling price for positive operating reserves (P^{pos}) specify the positive regulation benefit (PRB). The electricity available for a VPP (Ψ^{pos}) at time interval t based on the amount of stored electricity Q and the discharging speed δ is expressed by $\Psi^{pos}_{t,i} = \min(Q_{t,i}, \delta\Delta t)$. Besides also the cost for battery wear out is depreciated (D) over its effective use and the costs for charging C, including inefficiency ϵ, are taken into account. Moreover the opportunity costs of not being able to rent out the EV (RB) due to its commitment to a VPP in the current interval t and recharging it thereafter are considered (see Equation 6). Opportunity costs for recharging apply only if the next lessee cannot complete his expected trip with the reduced capacity from the VPP ($(Q_t - \Psi^{pos}_{t,i}) < \Delta Q_{t+j}$). The discharging inefficiency (η) also plays an indirect role as the amount of electricity consumed from the battery Ψ^{pos} is larger than the amount sold by $\frac{\Psi^{pos}}{\eta}$.

$$PRB_{t,i} = \Psi^{pos}_{t,i}\left[P^{pos}_{t,i} - \left(D + \frac{C}{\epsilon}\right)\right] - \sum_{j=1}^{\frac{\Psi^{pos}_{t,i}}{\delta t}} (RB_{(t+j),i,l} \mid (Q_t - \Psi^{pos}_{t,i}) < \Delta Q_{t+j}) \quad (6)$$

The offered selling price (P^{pos}) is composed of the depreciation cost (D), charging costs (C) including inefficiencies (ϵ), opportunity costs for rental and recharging time (RB) if the battery has insufficient capacity ($(Q_t - \Psi^{pos}_{t,i}) < \Delta Q_{t+j}$) for the lessee's purposes, and margin μ^{pos} which maximizes overall profits for the time intervals t in the test data set (see Equation 7).

$$P^{pos}_{t,i} = D + \frac{C}{\epsilon} + \sum_{j=1}^{\frac{\Psi^{pos}_{t,i}}{\delta t}} (RB_{(t+j),i,l} \mid (Q_t - \Psi^{pos}_{t,i}) < \Delta Q_{t+j}) + \mu^{pos}_t \quad (7)$$

FleetPower Decision Making at the Fleet Level. While it is important for lessees to rent a car at a specific location, the location within a city is less relevant for operating reserves. Rather than deciding for each EV individually where it should be deployed, we estimate an overall quantity for negative and positive operating reserves. This quantity comes from different EVs across the city and could switch within a time interval (t) from one EV to another if it is rented out.

Therefore we do not simply sum up the storage of each individual EV (Ψ) that could be committed to a VPP, but we correct this amount for the risk pooling effect (RPE). The risk pooling effect refers to better forecasts on the fleet level than at the individual car level. That means we predict how much overall storage should be used for positive and negative operating reserves. Then these amounts are allocated back to the individual EVs. This is why a VPP outperforms several EVs in isolation. The estimation for each operating reserve at the fleet level is based on a linear regression model with two independent variables. The first independent variable is the quantity of electricity available after the previous interval in the EVs (Ψ^{neg}/Ψ^{pos}) where the performance indicator suggested to charge (Equation 8) or turn the EV into a VPP (Equation 9). The second independent variable consists of the amount of electricity available in EVs where the performance indicator suggested negative or positive regulation in the last time interval, but where it would have been more profitable to rent out the EV. The term s refers to safety

Table 1: Table of Notation.

Variable	Description	Unit
a	Rental probability	$\frac{\%}{100}$
D	Battery depreciation cost	\$/kWh
d	Distance EV_i to closest EV	km
C	Electricity price (industry average)	\$/kWh
i	Specific EV	tag
I	Total number of EVs ($\sum i$)	
l	Location	ZIP code
P	Bid/offer price to buy or sell electricity from reserve market	\$/kWh
Q	Amount of electricity stored in an EV	kWh
q	Battery state of charge (Q/Ω)	$\frac{\%}{100}$
s	Safety stock	kWh
t	Time interval	index
Δt	Duration of a time interval	15 minutes
β	Regression parameter	
γ	Charging speed	kW
δ	Discharging speed	kW
ϵ	Charging inefficiency	$\frac{\%}{100}$
η	Discharging inefficiency	$\frac{\%}{100}$
μ	Margin on the bid/offer price	\$
Ψ	Electricity accessible within time interval	kWh
Ω	Maximum battery capacity	kWh

stocks that determine the trade-off between the risk of not renting out a car and missing out on potential profits on the reserve markets. The safety stocks (in combination with Equation 8 and 9) determine how many cars should not be committed as reserves. The optimization of the safety stock was done over the 7 week training period with the objective to maximize the overall profit. The safety stock grows with the asymmetric misclassification costs discussed in the previous section.

$$\begin{aligned} RPE_t^{neg} &= \beta + \beta_{n^{neg}} \sum_{i=1}^{I} (h(x) * \Psi_{t-1,i}^{neg}) \\ &+ \beta_{r^{neg}} \sum_{i=1}^{I} (j(x) * \Psi_{t-1,i}^{neg}) - s \end{aligned} \tag{8}$$

$$\begin{aligned} RPE_t^{pos} &= \beta + \beta_{n^{pos}} \sum_{i=1}^{I} (k(x) * \Psi_{t-1,i}^{pos}) \\ &+ \beta_{r^{pos}} \sum_{i=1}^{I} (m(x) * \Psi_{t-1,i}^{pos}) - s \end{aligned} \tag{9}$$

where:

$$h(x) = \begin{cases} 1, & if \quad PPI_{t-1,i} = NRB_{t-1,i} \\ 0, & otherwise \end{cases} \tag{10}$$

Table 2: Descriptive Statistics Car2Go Dataset.

Description	Value
EV type	Smart Fortwo Electric
Max. battery capacity (Ω)	16.5 kWh
Electricity costs (C)	0.1155\$ (Band IC)
Battery depreciation cost (D)	0.13 \$/kWh (2015) 0.067 \$/kWh (2018) 0.034 \$/kWh (2022)
Charging speed (γ)	3.6 kW (linear)
Discharging speed (δ)	13.2 kW (linear)
Charging inefficiency (ϵ)	96% (Reichert 2010)
Discharging inefficiency (η)	97.4%
	Min. / Avg. / Max.
EVs available (a)	13% / 85% / 97%
Rental revenues	4.89 \$ / 20.04 \$ / 322.34 \$

$$j(x) = \begin{cases} 1, & if \quad PPI_{t-1,i} = NRB_{t-1,i} \\ & and \quad RB_{t-1,i} > NRB_{t-1,i} \\ 0, & otherwise \end{cases} \tag{11}$$

$$k(x) = \begin{cases} 1, & if \quad PPI_{t-1,i} = PRB_{t-1,i} \\ 0, & otherwise \end{cases} \tag{12}$$

$$m(x) = \begin{cases} 1, & if \quad PPI_{t-1,i} = PRB_{t-1,i} \\ & and \quad RB_{t-1,i} > PRB_{t-1,i} \\ 0, & otherwise \end{cases} \tag{13}$$

The actual allocation of individual cars is done in the order of profitability according to PPI, until the respective overall quantities $\sum_{i=1}^{I} \Psi^{neg} - RPE^{neg}$ and $\sum_{i=1}^{I} \Psi^{pos} - RPE^{pos}$ are reached. Each quantity is submitted to the operating reserve market at the average price from Equations 5 and 7 weighted by the quantities for the individual prices respectively.

Design Evaluation: Evidence from a Real World Setting

In order to assess the economic viability of the above described algorithm in practice, we apply it to the carsharing service Car2Go of the Daimler AG. We use a seven week time period from 08.11.2013 till 27.12.2013 as a training data set (bootstrap period). From this training set the expected values for the average driven kilometers, rental time, rental profit, and rental probabilities at each time are used to train the model. The last four weeks from 28.12.2013 to 24.01.2014 are used to evaluate the model.

Carsharing Operator: Car2Go

The free floating fleet of Car2Go in Stuttgart, Germany consists of 500 EVs. These EVs are distributed over 54 zip codes of Stuttgart and its surrounding area. Members pay for this service on a use basis only (per minute and km above a threshold of 50 km) and are incentivized to return EVs to a charging station when the battery status is below 30% by rewarding them with 20 free driving minutes.

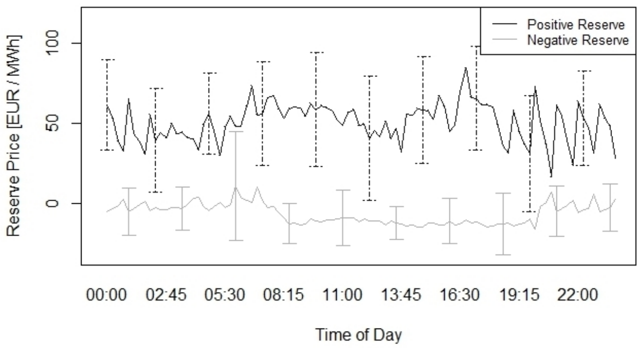

Figure 1: Daily Operating Reserve Prices from 08.11.2013 to 24.01.2014.

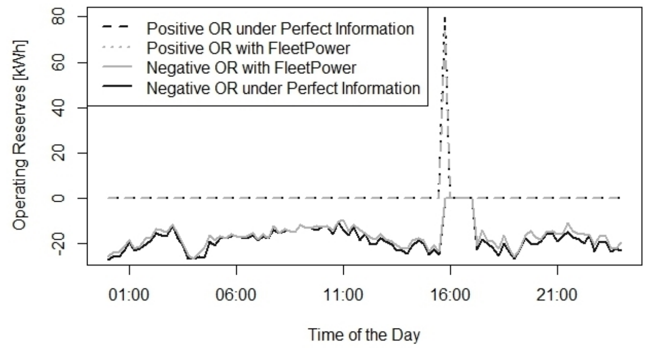

Figure 2: Virtual Power Plant Output for the 5th of January 2014.

The carsharing operator shared data with us for the availability of EVs with a granularity of 15 minutes. This data contains the unique car name, the geo coordinates where the car is parked, the street name and zip code of that location (l), the state of charge of the battery (Q), and whether the EV is currently charging. Based on this information we can infer how long the EV was rented, how many kilometers were driven, and how much revenues were earned as rental benefit (RB). For an overview of the dataset see Table 2.

Secondary Operating Reserves: Transnet BW

As illustrated in the section Operating Reserves EV storage is particularly suited for the secondary operating reserve, due to its fast response requirement. Therefore we use auction data on secondary operating reserves to determine the prices for balancing at each point in time. We use the data from regelleistung.net, the German operating reserve operator for the region of Transnet BW (see Figure 1). Note that even though the profits from renting out EVs are higher on average, the commitments on the operating reserve markets take precedence over renting because a severe penalty is imposed for not living up to commitments. As a consequence rental profits that occurred in the dataset, while the algorithm committed these EVs to the VPP, are opportunity cost. Only if another, available EV was in the immediate vicinity this car was assumed to be taken instead. Immediate vicinity is interpreted as if customers were willing to walk to another car if it is less than normally distributed with a mean of 250 meters and a standard deviation of 100 meters away (d) as calculated with the haversine formula (Robusto 1957).

Fitting the Model to the Case

We train the model for the expected rental benefit (Equation 2) from 7 weeks of Car2Go rental data. It suggests that being at a place and time where EVs frequently get rented out has a strong positive impact, and lower battery levels have a negative impact on rental profits. To account for the asymmetric payoff from rental (average benefit per rental is \$ 20.04) and operating reserves (average benefit is \$ 0.40) we use the upper 99% confidence level to overstate the rental benefit accordingly.

After we have fitted the model for the individual performance indicators to the Car2Go case, we can train the fleet level decision making model with information from the individual EVs. At popular time intervals, and therefore adjacent intervals, fewer cars (stored electricity) are available but many will be rented out. In a similar way the stored electricity is positively related to the number of EVs rented out in the previous time interval. In this case we use both an upper 99% confidence interval and a safety stock s of 56 and 33 kWh respectively for positive and negative operating reserves which was optimal during the test period.

Operating Reserve Markets: Design for Flexibility

Current operating reserve markets use dedicated idle capacity as operating reserves which are committed a week in advance. It is not only inefficient to have that much idle reserve, but it is also not fit to balance a market with large capacities of decentralized energy sources. Therefore we propose and use an alteration of the market design. In this design power comes from a critical mass of flexible, absorptive generation and storage capacity, rather than having fixed commitments one week in advance. This has the advantage that battery storage can offer additional reserves to the market to meet growing demand. Note that this market design is not risk free. It depends on the availability of sufficient flexible absorption and generation capacity, like storage in batteries that is elastic to price changes.

Analysis and Discussion

Over the four week hold out period the algorithm made 154,445 EV management decisions, of which it decided in 75,813 instances to turn an EV into a VPP (49%). Of these 75,813 instances only 89 were for providing positive regulation capacity and 75,724 instances were for providing negative regulation capacity. In 109 of these instances a lessee wanted to rent an EV while it was committed as a VPP; in 69 of these instances there was a car in walking distance. That means that we had to refuse lessees in 40 instances over the four week time period translating into a gross profits reduction of 0.125%. At the same time the algorithm traded 61 MWh on the operating reserve market, increasing the gross

Table 3: Sensitivity Analysis for Different Balancing Needs and Battery Technology Developments.

	Balancing Need Today	**Balancing Need x2**	**Balancing Need x3**
Battery Technology 2015	↑ 7.18% gross profit	↑ 8.75% gross profit	↑ 11.44% gross profit
Battery Technology 2018	↑ 7.20% gross profit	↑ 8.90% gross profit	↑ 11.81% gross profit
Battery Technology 2022	↑ 7.23% gross profit	↑ 9.05% gross profit	↑ 12.11% gross profit

profits of Car2Go by about 7.18% assuming capital costs are 60% of rental revenues (industry average). This increase is significant at the 0.01 significance level (p-value 0.002). The negative operating reserves account for virtually all the increased gross profit (99.8%). This can be traced back to the high battery costs, which are higher than the average positive operating reserve price. When we compare this to a case in which Car2Go has perfect information on future usage of EVs, we see that FleetPower makes almost optimal decisions. With perfect information they would increase gross profits by about 8%. The relatively high accuracy of FleetPower can mostly be attributed to the risk pooling by substituting committed EVs for operating reserves with other available EVs if a lessee wants to rent a specific EV. If we were to make this decision for each EV individually, we would increase gross profits by only 0.07%. One can conclude that using FleetPower is significantly more profitable then only renting out EVs and comes close to a scenario where the fleet owner has perfect information. Figure 2 illustrates at which times of the day FleetPower turns EVs into a VPP and how much output it produces. Most of the day the EVs provide negative reserve capacity, but at 16.00 PM the market price is high enough for the VPP to provide positive reserve capacity.

Planning for Change: A Sensitivity Analysis

In order to assess how rapid developments in the energy sector will influence the decisions and their profitability in the future, we consider three scenarios for future balancing needs. In the first scenario we consider the current market need for balancing, in the second scenario we consider market prices when the balancing need goes up twofold, and in the third scenario we consider market prices when the balancing need goes up threefold. The scenarios are derived by multiplying the balancing demand per time interval by 2 and 3 respectively, which increases volatility proportionately along the merit order. Besides the balancing requirements, also a change in the costs of battery technology is expected. This is due to a large investment in battery technology not only for EV but also laptops, mobile phones, and other applications. We consider three scenarios for the battery depreciation costs. The first scenario of 0.13$/kWh is likely to be achieved by 2015, the second scenario of 0.067$/kWh is likely by 2018, and the 3rd scenario of 0.034$/kWh is likely by 2022 (US Department of Energy 2013).

As expected we see a steady increase in profits for fleet owners with increasing balancing needs and decreasing battery costs from initially a 7.18% gross profit increase to 12.11% under the 2022 scenario. At first glance it might seem as if the increase in the balancing need is more decisive than the battery technology. However, battery costs only have an influence on positive operating reserves, which account for about 0.2% today and 14% under the 2022 scenario. Therefore the impact appears relatively minor, but it increases as the positive operating reserves play a bigger role. For an overview of the gross profit increases for the individual scenarios see Table 3. While under current conditions it would hardly be economical to base positive operating reserves on EV storage only, it does make sense in the 2022 scenario. In that case about every 20th person would need to have an EV that participates, but is not dedicated to the operating reserves. Under these circumstances one could retire all peaking power plants in the secondary operating reserve market, reducing the peak to average ratio by 4.5%. The peak to average ratio is the bottleneck in the electrical grid and determines its efficiency. When we relate this to increasing energy efficiency, we find that despite efficiency losses when charging and discharging EVs, the overall efficiency achieved by retiring peaking power plants offsets these losses and increases overall system efficiency.

Conclusion and Future Work

In this study we have proposed and evaluated the agent-based algorithm FleetPower which enables companies with EV fleets to participate in the operating reserve market next to renting out electric vehicles (EV). It continuously makes the decision whether a specific EV at a specific location should be available for rent, or to sell part of its energy storage as negative or positive operating reserve. The algorithm makes this decision based on forecasts for revenues from rental, positive, and negative operating reserves and aggregate EV availability in VPPs with an accuracy above 99%. We show that using EV for operating reserves enhances gross profits of the EV fleet owner by 7.18%, but that the market design of the operating reserves needs to change for more flexibility to tap into the potential of large scale storage of EVs. V2G currently accounts for only a marginal proportion of these additional profits, while 99.8% are due to negative operating reserves. With a rising need for balancing capacity and decreasing battery costs, also V2G will account for a higher share (14%) of the increase in gross profits by 2022. In total the gross profits for EV fleet owners could go up by as much as 12.11% by 2022. With this algorithm it is possible to replace carbon intensive generation capacity with clean energy storage in the future, which increases system efficiency (peak to average ratio) by 4.5%.

In future research we will analyze the influence of seasonality on the ability of EVs to replace peaking power plants. In addition we expand the analysis with tow cities in the US and NL to account for different levels of renewable energy sources. Finally we plan to implement the broker in Power TAC to compete with and benchmark against other brokers.

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