BALANCING WITH ELECTRIC VEHICLES: A PROFITABLE BUSINESS MODEL

Micha Kahlen  
*Erasmus University Rotterdam, Rotterdam, Zuid-Holland, The Netherlands*, kahlen@rsm.nl

Wolfgang Ketter  
*Rotterdam School of Management, Erasmus University, Rotterdam, Netherlands*, wketter@rsm.nl

Jan Dalen, van  
*Erasmus University Rotterdam, Rotterdam, Zuid-Holland, Netherlands*, jdalen@rsm.nl

Follow this and additional works at: [http://aisel.aisnet.org/ecis2014](http://aisel.aisnet.org/ecis2014)
BALANCING WITH ELECTRIC VEHICLES: A PROFITABLE BUSINESS MODEL

Complete Research

Kahlen, Micha, Rotterdam School of Management, Rotterdam, The Netherlands, kahlen@rsm.nl
Ketter, Wolfgang, Rotterdam School of Management, Rotterdam, The Netherlands, wketter@rsm.nl
Dalen van, Jan, Rotterdam School of Management, Rotterdam, The Netherlands, jdalen@rsm.nl

Abstract

Virtual Power Plants (VPP), centrally-controlled systems of interconnected energy sources, are relevant for balancing the electrical grid. VPPs facilitate flexible energy supply through distributed generation, storage capacity and demand response mechanisms. In our research, we study the role of VPPs consisting of electric vehicles (EV) fleets in addressing the challenges associated with inflexible renewable energy sources. Idle EV’s objectives are charging for the next ride and providing VPP capacity, which we show is sufficiently available. These VPPs participate in an energy exchange. They are controlled by intelligent trading agents which buy energy on the spot market, store it, and sell it later at higher prices. We study trading behavior of EV fleet owners agents, and its effects in Power TAC, a large scale, multi-agent smart grid simulation. We show that these VPPs offer crucial resource flexibility to the grid. They reduce the average electricity price by 3.2% and CO₂ emissions by 2.4%. In addition, we show how increasing competition among VPPs affects profitability for fleet owners. The key contribution of this research is the validation of a VPP business model in terms of its profitability through arbitrage, ecological worthwhileness through emission reductions, and benefits for consumers by reducing energy expenses.

Keywords: Smart Grid, Agents, Electric Vehicles, Virtual Power Plant.

1 Introduction

Advancing depletion of fossil fuels and soaring oil prices have induced a rapid growth of volatile renewable energy sources. Large differences in production and consumption of energy destabilize the grid leading to black outs. As a consequence, balancing the grid plays a central role in reaping the potential of volatile, renewable energy sources. Smart grids provide a framework for balancing by providing information on the requirements in supply as well as demand in energy. With an increasing adoption of Electric Vehicles (EV), storage capacity for electricity becomes available. It has been suggested to employ this capacity to offer balancing services to the grid (Wolfson et al., 2011, Ramchurn et al., 2011b, Peterson et al., 2010, Reichert, 2010). This balancing can be coordinated with smart grid price signals on the energy market. Intelligent trading agents, that represent fleets of EVs aggregated to Virtual Power Plants (VPP) act on these signals (Asubel and Crampton, 2010). VPPs are a collection of distributed energy sources that are centrally managed and aim to generate power at consumption peaks. They purchase energy on the spot market to charge their EVs in a combination
with futures to sell this energy at a later point in time for a higher price. We present a trading strategy in which agents use the capacity of idle EVs to form a VPP. Part of this problem has already been addressed for static battery storage by Vytelingum et al. (2011). However, intermittently-connected EVs that also consume energy differ substantially from static battery storage and a analytic solution cannot answer the question in the case of EVs. Therefore we study the effects of this trading in the Power Trading Agent Competition (Power TAC), a large-scale smart grid simulation. In Power TAC multiple self-interested trading agents (brokers) compete on the energy market representing energy suppliers, energy retailers, energy consumers, and VPPs. This way we do not only consider the interests of the fleet owner but also that of other market participants and how they influence the VPP agents decision. In the simulation one observes that the actions of agents controlling VPPs have a positive effect on the triple bottom line (United Nations, 1992). It lowers energy prices for consumers (people), it mitigates \( CO_2 \) emissions (planet), and offers profits for fleet owners (profit).

2 Background and Related Work

2.1 Smart Grid Business Model

The core of this research is based on EV fleet owners acting as VPPs by aggregating the capacity of their idle EVs. The intelligent trading agents (Bichler et al., 2010) that control the VPP employ the otherwise idle batteries to absorb peak demand in electricity consumption. In doing so, the agents have two complementary objectives. On the one hand they have to minimize procurement cost for energy to charge the VPP. On the to achieve their driving goals. The agents fulfill these objectives by looking at the price in the spot market, as well as strike prices for futures in the day ahead market. Trading decisions are based on the price differences across time. This requires only a slight reconfiguration of current business models of EV fleet owners as only idle capacity is used and therefore all benefits earned through this trading are on top of already existing business models. A positioning of the agent based algorithm in its context is done in Figure 1. For scope reasons we do not take business process reengineering into account as the need for this largely varies per company and is to a large extend mandated by a transition to smart grid infrastructure regardless of this business model.

The business model can be classified as what Hevner et al. (2004) describe as design science. We create an information system artifact in form of a trading model that couples the emerging technology of EVs with energy markets. This artifact addresses the challenges of the future energy landscape and we apply the knowledge base of agent based simulations to evaluate the artifact in terms of the triple bottom line. That way we contribute to the embedment of the role of EVs in energy systems and add to

![IS Trading Algorithm](image)

*Figure 1. Overview of the business model in its context.*
the agent simulation knowledge base. This is especially relevant for the information system community, as environmental sustainability, has remained so far unaddressed in the top information system research journals, while IS plays a critical role in reducing impacts on the environment and climate change (Melville and Nigel, 2010).

2.2 Volatile Energy Sources and Balancing

Energy providers are faced with a resource allocation problem. Increasingly volatile supply and fluctuating demand makes it difficult to predict when to deploy energy storage and additional generators. But also making demand more flexible, especially in cities and industrial areas is important for energy providers (Appelrath et al., 2012). One approach is to employ time of use (TOU) pricing by targeting the consumer’s price elasticity (Kim et al., 2012, Faruqui et al., 2011, Sioshansi, 2012). For the long term stability of the electricity market previous research pointed out that capacity markets can address the resource adequacy problem. However, for short term balancing it needs to be combined with a reserve power market (Crampton and Ockenfels, 2012). We put our focus on short term balancing.

2.3 Role of EVs in the Smart Grid

A large number of EVs is predicted to have a problematic effect on the grid at the distribution level: transformers and substations at the regional level can be overloaded quickly when not adequately managed. In contrast, the average additional demand for charging is no significant problem to the generation capacity in the long term (Kim et al., 2012, Faruqui et al., 2011, Sioshansi, 2012). To solve this problem Valogianni et al. (2012) suggest smart charging to use price incentives that regulate the problematic effects for the transformers and substations.

Fleet owners with large quantities of EVs can manage the demand side of electricity by charging their cars (Gottwald et al., 2011, Ramchurn et al., 2011b). In addition, fleet owners can influence the supply side by making additional energy available to the grid during demand peaks, also referred to as Vehicle-to-Grid (V2G). Vytelingum et al. (2011) investigated these effects at the household level and illustrate a 14% saving in the energy bill - while also reducing carbon emissions by 7%. These findings are consistent with Ramchurn et al. (2011b) who estimate a 14.5% reduction of the energy expenses for a household. Other studies find that the yearly benefits are in the range of $20-120 (approximately €16-96) (Peterson et al., 2010) and €135-151 (Reichert, 2010).

A price sensitivity analyses conducted by Reichert el al. (2010) shows that at a price of 50 €/MWh for battery degradation cost, batteries are hardly used for storage, whereas it is profitable at 10 €/MWh. The usage of VPPs of EVs therefore depends on future developments in battery technology.

There are two conflicting opinions about the profitability of VPPs of EVs. Some argue that the low yearly profits for individuals from load balancing would not make it commercially successful (Peterson et al., 2010). In contrast, others perceive this approach as a new way to make volatile renewable energy sources suitable for mainstream energy usage. This is due to the ability to hedge the volatility with a large amount of EV batteries (Ekman, 2011). We concur with the latter position as with increasing renewable energy sources also volatility and therefore electricity prices will increase, leaving more room for financing business models that build on electricity storage.

3 Model Description

In order to study the effect of the business strategy for balancing services we focus on the energy wholesale market. In the wholesale market also other, self-interested brokers, buy and sell energy in the deregulated energy market with the main objective to make a profit.
3.1 Wholesale Market Environment

We consider an energy market with a spot market for electricity at every hour and a day ahead market which determines the price for electricity up to 24 hours ahead at every hour. In the day ahead market we focus on futures, which are agreements in which two parties agree at every hour to exchange a specified amount of energy at the delivery date (hour) for a certain strike price.

The prices on the energy market are determined after the North American model with a periodic double auction analogous to (reverse) multi-unit auctions, in which multiple buyers and sellers participate (Krishna, 2002). Suppliers submit an "ask", that states the quantity \( Q_a \) they would like to sell and the lowest price \( P_a \) they are willing to accept, for the specified hour \( t \). The buyers place a "bid" that states the quantity \( Q_b \) they want to buy and an indication of the price \( P_b \) they are willing to pay at most for the specified hour. Once all "bids" and "asks" are placed, all "asks" for a certain hour are ordered by ascending price to estimate the supply curve. All "bids" for a certain hour are ordered by descending price to estimate the demand function. The intercept of both functions is the clearing price that matches supply and demand. This clearing procedure determines the price \( P \) for electricity in our simulation. For an example clearing see Figure 2.

By employing demand and supply functions to determine the electricity price we can monitor the impact of large EV fleets on the electricity market. This is desirable because possible peaks caused by uncoordinated EV charging are difficult to balance and can lead to system instability.

3.2 Role of EV fleet Owners in the Energy Wholesale Market

Prices for futures on the wholesale market vary from one hour to another. Large fleet owners with storage capacity at their disposal can benefit from this temporal price variation. Both, selling and buying, has an impact on the clearing price and quantity for that hour. On the one hand large fleet owners place "asks" on the market, which increases supply leading to a larger clearing quantity and a price decrease. On the other hand when fleet owners place "bids" on the market, the demand increases leading to an increase in both the clearing quantity and price.

![Example clearing wholesale market.](image-url)
3.3 Decision Making Software Agents

Intelligent software agents are deployed to optimize the energy trading and grid balancing capacity on the wholesale market. These trading agents conform to the weak notion of an agent (Bichler et al., 2010). Many authors advocate the use of intelligent trading agents for demand side management in the smart grid (Ramchurn et al., 2011a, Ramchrun et al., 2011b, Vytelingum et al., 2011, Gottwald et al., 2011). They automate trading in the energy wholesale market in the interest of the fleet owners. As the fleet owners primary business is renting vehicles to customers, an agent can only use an electric vehicle if the car is idle and are sufficiently charged for the next trip. We assume that the agents have perfect information about planned trips. It could get this information from a reservation system, historic driving data, and possibly even an integration with the drivers calendar. To account for the inaccuracy of this assumption for the model we use a 10% battery safety margin, which allows to cover average trip length.

3.4 Prosumer Strategy

When intelligent software agents trade energy for EV fleet owners on the wholesale market they have to act in their best interest. Therefore we elicited one possible prosumer strategy for agents that maximizes the profits for fleet owners without compromising individual mobility. This strategy prescribes the intelligent agent’s trading behavior and specifies general rules when charging the fleet and when selling energy back to the grid is more beneficial.

The profit maximization objective can be noted as follows:

\[ \arg \max_{D, G} \sum_{t=0}^{T} (D_t \times P_t) - (G_t \times (P_t - B)) \]

where \( D \) is the amount of energy discharged and available for the grid, \( t \) is the specific hour, \( T \) is the number of hours over which we maximize, \( P \) is the price for energy, \( G \) is the amount of energy charged to the battery, and \( B \) is the battery depreciation cost. So we maximize the profits the agent makes by optimizing the revenues he makes from selling energy in each hour and the costs it incurs from charging its fleet in each hour plus the battery depreciation cost.

The agent has to take into account the following when maximizing the profit:

3.4.1 Discharging

\[ 2) \quad D_t = \sum_{i=0}^{t} d_{i,t} \times e_D \]

where \( d \) is the amount of energy discharged from the battery, and \( e_D \) is the percentage of efficiency for discharging. Equation 2 represents the total amount of energy that is discharged during a specific hour and made available to the grid. It also ensures that a charging inefficiency is taken into account. When energy is converted from direct current to alternating current and stored a certain percentage of energy is lost.

3.4.2 Charging

\[ 3) \quad G_t = \sum_{i=0}^{t} g_{i,t} \times e_G \]

where \( g \) is the amount of energy taken from the grid for charging, and \( e_G \) is the percentage of efficiency for charging. Equation 3 represents the actual amount of energy that is charged to a certain battery storage level. It also ensures that a discharging inefficiency is taken into account. When energy is converted from alternating current to direct current a certain percentage of energy is lost.

\[ 4) \quad G_{i,t}, d_{i,t} \leq S_{i,t} \times a_{i,t} \]
where $S$ is the storage level of a battery at the beginning of an hour, and $a$ is the availability (binary) of an EV. Equation 4 makes sure that the capacity used for charging and discharging is available at the specified hour.

$$5) S_{i,t} = S_{i,(t-1)} - D_{i,(t-1)} + G_{i,(t-1)} - A_{i,(t-1)} \geq 0$$

where $A$ is the amount of energy used for driving. Equation 5 takes care of the electricity storage levels of EVs. It accounts for storage capacity left from previous hours, charging and discharging that occurred in the previous hour, and that energy was used for driving in the previous hour.

$$6) A_{i,t} = K_{i,t} * F_i$$

where $K$ are the km driven, and $F$ is the fuel efficiency. Equation 6 defines the energy that is used for driving by the kilometers that a certain car drivers in a certain hour times the fuel economy

$$7) \alpha_i \leq S_{i,t} \leq \omega_i$$

where $\alpha$ is the minimum storage of an EV, and $\omega$ is the maximum storage capacity of an EV. Equation 7 states that a battery cannot be under or over charged.

$$8) S_{i,t} \geq A_{i,t}$$

Equation 8 ensures that an EV can only drive until the battery is empty.

$$9) A_{i,(t-1)} \leq S_{i,t} - D_{i,t} + G_{i,t} - A_{i,t}$$

Equation 9 makes sure that an EV will always be sufficiently charged for planned trips.

The price for energy is determined dynamically, depending on the forces of demand and supply as explained in section 3.1. Observe that the agents that coordinate the VPP are no price takers. By participating in the market they influence demand and supply and have an effect on the clearing price because of their market share.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>t</td>
<td>the hour that specifies the delivery date for the energy contract</td>
</tr>
<tr>
<td>T</td>
<td>the number of hours over which the problem is maximized</td>
</tr>
<tr>
<td>D</td>
<td>amount of energy discharged and available for the grid</td>
</tr>
<tr>
<td>i</td>
<td>a specific EV</td>
</tr>
<tr>
<td>P</td>
<td>energy price</td>
</tr>
<tr>
<td>I</td>
<td>number of EVs in the market</td>
</tr>
<tr>
<td>G</td>
<td>actual amount of energy charged to battery storage level $S$</td>
</tr>
<tr>
<td>B</td>
<td>battery depreciation costs over life cycles</td>
</tr>
<tr>
<td>d</td>
<td>amount of energy discharged from battery storage level $S$</td>
</tr>
<tr>
<td>eD</td>
<td>percentage of efficiency for discharging</td>
</tr>
<tr>
<td>g</td>
<td>amount of energy taken from the grid for charging</td>
</tr>
<tr>
<td>eC</td>
<td>percentage of efficiency for charging</td>
</tr>
<tr>
<td>a</td>
<td>availability of an EV</td>
</tr>
<tr>
<td>S</td>
<td>storage level of a battery at the beginning of an hour</td>
</tr>
<tr>
<td>A</td>
<td>amount of energy used for driving</td>
</tr>
<tr>
<td>K</td>
<td>km driven</td>
</tr>
<tr>
<td>F</td>
<td>fuel efficiency</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>minimum storage capacity of an EV</td>
</tr>
<tr>
<td>$\omega$</td>
<td>maximum storage capacity of an EV</td>
</tr>
</tbody>
</table>

Table 1. Table of notation equation 1-9.
The above maximization problem defines the trading objective for the trading agent. For sake of simplicity we abstract from the above objective function by not accounting for each EV individually and use an aggregate of all EVs. We will show in the analysis section that this does not have an effect at the macro level. We also assume that the infrastructure is in place to charge an EV within one hour. In order to be able to evaluate the impact of this trading strategy we need more specific market data, which will be discussed in the following section.

4 Data and Methodology

This section covers the data acquisition and methodology part. We simulate a wholesale market in which we are able to control the electric vehicle penetration and model customers with realistic driving profiles. We compare the situation of the wholesale market with and without VPPs of EVs and evaluate it against the triple bottom line concept. The impacts on the social welfare in terms of electricity price reductions (people), carbon emission reductions (planet), and financial sustainability of the trading strategy (profit) are studied in this paper. We use a simulation to study the effects, because the physical infrastructure for this business model is still under construction, and pilot projects cannot capture the dynamic effects of large fleets of EVs. In this section the methods that we use to validate the results are explained.

4.1 Testbed: Power TAC

The Power Trading Agent Competition (Power TAC) is the testbed to our simulation environment (Ketter et al., 2012b). It is a state of the art competitive simulation of a smart grid energy market. Brokers, which represent for example electric utility companies, trade energy on both future retail and wholesale market. It is unique as it models individual customer behaviors, their valuations for energy tariffs and risk preferences, as well as a day ahead energy market like the EEX or FERC.

We use Power TAC because it is a decentralized smart grid simulation; its realism and robustness have been proven by previous research (Ketter at al. 2013a, Ketter et al. 2013b, Ketter et al. 2012a). In Power TAC the competitive retail and wholesale energy market is simulated for a city. On the retail market different brokers offer energy subscriptions to households and commercial customers. These customers have smart meters, different consumption patterns (for example they are weather dependent), and preferences for flat or variable pricing schemes. The brokers purchase energy to meet their customers demand on the wholesale market. The wholesale market functions like a energy wholesale market in the US or Europe with a spot and a day ahead market. On this wholesale market the brokers place bids and ask together with large producers of energy as described in Section 3.1 for the next 24 hours. In case the broker cannot match its customers with purchased capacity the distribution utility, which operates the physical facilities, penalizes the broker by the amount that the distribution utility has to purchase on the regulating market. All brokers are intelligent trading agents from different Universities competing for profitability. Even though these brokers are self-interested, the market design contributes to a smooth functioning of the market that includes renewable energy sources, market stability, and affordable energy prices. We extent this model with an additional broker that does not get its revenues from customers but from VPPs of EVs that charge in cheap hours and provide energy to the grid at premium prices.

1 www.powertac.org
4.2 Driving Profiles

We augment Power TAC with VPPs of EVs, aggregated by fleet owners. In order to know how large the VPP is we do not only need to know the fleet size, but also the information on when the EVs are idle, waiting to join the VPP. The balancing capacity for the VPP is a function of the number of EVs in the fleet adjusted for customers driving usage of the leased car. Given that EVs are more likely to be used in an urban context we are especially interested in car behavior that reflects an urbanized driving style. Therefore we consider driving behavior from the Netherlands, which is one of the most densely populated countries in the world. A mobility survey by CBS, the Dutch Statistical institute\(^2\), from 1999 with 63,336 respondents (71.2% response rate) through 2007 with 23,240 respondents (70% response rate) gives us insights in the usage of cars. We assume that driving behavior for EVs will not be significant different once the battery technology allows longer driving ranges. When analysing customer driving patterns one can clearly see the peaks in driving behavior from 7 a.m. to 9 a.m. and 4 p.m. to 6 p.m. during rush hour (see Figure 3). Furthermore we distinguish between weekdays and weekends, as the data implies that people drive less during weekends than during the week. Based on those driving patterns we can infer how much each car needs to be charged in different hours, which is reserved capacity that cannot be used for trading. Finally we account for the fact that an EV cannot be plugged in everywhere. So even if the cars are idle, they are not connected to a charging station because they are physically not available. We therefore account for a 90% capacity constraint (10% of the idle capacity of EVs is not available to the VPP) as suggested by Fluhr (2008).

4.3 Battery Costs and Conversion Losses

As the developments in battery technology are the crucial factor in determining profitability (Schill, 2011), but are difficult to predict, we consider two scenarios in battery development. For both scenarios we consider a 16 kWh lithium ion battery. The scenarios are based on the blueprint \textit{EV Everywhere} of the US Department for Energy which outlines objectives for battery capital cost reductions from currently €370/kWh ($ 500/kWh) to €90/kWh ($ 125/kWh) in 2022 (US Department of Energy, 2013). In the first scenario we consider the intermediate capital costs of €140/kWh, in the second scenario we consider the 2022 scenario (€90/kWh). For the VPP application of the battery it is

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure3.png}
\caption{Average driving distance for an average Monday in the Netherlands}
\end{figure}

\(^2\) www.cbs.nl
particularly important to make accurate cost allocations. This way the battery wear out costs due to trading do not additionally increase the costs for driving. Therefore we depreciate the battery capital costs over its effective life cycles. Currently lithium ion batteries need to be replaced after 2500 life cycles\(^3\) (Smith et al., 2013). We assume that with technological improvements the number of life cycles that a battery can be used before replacement will increase to 2900 cycles for scenario 1 and to 3800 cycles in scenario 2. Whenever an agent trades, it needs to account for the wear out depreciation costs for the battery capacity it uses for that transaction. The corresponding depreciation cost amount to €0.048/kWh for scenario 1, and €0.024/kWh for scenario 2.

The energy conversion efficiency is an important cost aspect to consider as well when evaluating the VPP’s profitability. About 3–4\% of the energy is lost during the charging process of the EV as the alternating current from the grid has to be converted to direct current and subsequently be stored in the battery (Reichert, 2010). When energy is delivered to the grid from the EVs battery 2.4\% of the energy is lost because it has to be re-converted from a direct current to an alternating current using an off the shelf solar energy inverter\(^4\). Every time the VPP is used we have to account for these costs to get accurate estimates of the actual benefits.

### 4.4 Monte Carlo Optimization

With the previously described model, enriched with market and customer data, fleet owners agents are faced with an optimization problem. They know the prices for the next 24 hours and know when they have how many EVs available to form VPPs. However, they want to know at which hours they should charge EVs (and how much) and when they should make energy available for sale (and how much). We solve this problem with the help of the Monte Carlo optimization method (Dickman and Gilman, 1989). First we generate asks and bids for energy on the wholesale market, so they randomly sell and buy energy over a period of 24 hours. This buying has an effect on the market price for energy as described in the section 3.1. The VPP agents will use the most profitable outcome to make their sales and purchases. The Monte Carlo approach is most suitable for the maximization problem at hand, as the problem space is large and it allows to search for global maxima. The complexity of the problem lies in the pricing mechanism: by selling and buying a certain quantity of energy the agents influence the clearing price for energy, which in return influences the optimal selling and buying amount. Therefore a linear programming solution is not possible in this case.

The method can principally be generalized to the trading of all goods on financial markets. However, the benefits in electricity markets are most promising because price differences across hours are large since the market is not able to arbitrage the difference without appropriate storage (considering a market without VPPs of EVs).

### 4.5 Statistical Methods

The simulation can be controlled in terms of EV market penetration. This allows for a comparison of wholesale market clearing prices with and without EVs present. To investigate whether there are significant differences between both settings we apply paired t-tests for means and two sample F-tests for variances. Despite the fact that the simulation is a non-terminating system it needs to be considered as a terminating system to be able to run statistical tests on it. The warm-up period is 14 days, which is standard in the Power TAC environment. The warm up period ensures that initial values such as for example the initial battery charging level do not influence the simulation results. In order to determine

\(^3\) at a depth of discharge (DoD) of 80\% and assuming batteries will be replaced when capacity is reduced to 80\% of the original

\(^4\) SUNNY CENTRAL 100 outdoor/100 indoor: [http://www.sma-america.com](http://www.sma-america.com)
how long the simulation has to be run we use the sequential procedure (Law and Kelton, 2000): The 95% confidence interval of the profit has a half-length of less than 5% of the mean with at least 183 replication days. So we have to run the simulation for at least 183 time days to get reliable results.

5 Analysis: Triple Bottom Lines

This section analyses the results of our simulation. It evaluates and explains the effects of VPPs consisting of EVs on the wholesale market in terms of the triple bottom line. First we evaluate the financial viability under competition (profit), then we analyze the effects on the electricity price for consumers (people), and finally we illustrate the impact on carbon emissions (planet).

5.1 Profit: Fleet Perspective

To evaluate the profitability of VPP for fleet owners, we first consider a situation with a low EV penetration rate (<10%). Under scenario 1 fleet owners make an average annual profit of €50 per EV; this profit increases to €150 per EV in scenario 2. When comparing these findings to the studies of Peterson et al. (2010) and Schill (2011) who found €16-96 and €135-151, respectively we can conclude that the findings are similar even though we did not model EV batteries individually. However, this abstraction in our model allows us to see the effects of competition on the macro level.

The simulated wholesale market assumes perfect competition. Equilibrium prices are determined by supply and demand of many actors. No single participant can set the prices for electricity. However, at the aggregate actors do have an effect on the market. As we can see in Figure 4, the market experiences diminishing returns for every additional EV that enters the market. Another way to interpret this is that benefits per EV at low EV penetration rates are much larger as compared to high penetration rates. This effect rewards early adopters, when penetration rates are low, with premium returns.

![Figure 4. Adverse effects of competition.](image)

![Figure 5. Total yearly profits in the Dutch market under Scenario 1 and 2.](image)
Although individual returns decrease, total profits in the market increase with each additional EV. When examining the total profit in the market under both scenarios, we see that total profits in the market reach a saturation level when at least 57% of vehicles\(^5\) are EV participating in VPPs (see Figure 5). For the example of the Netherlands that would mean about 4.3 million EVs. At this level of competition fleet owners participating in VPP trading under scenario 1 make a profit between €0.0108/kWh and €0.012/kWh traded assuming a 95% confidence interval. This translates in yearly profits per EV of €16. Under scenario 2 with lower battery depreciation costs fleet owners would earn between €0.0215/kWh and €0.0238/kWh (95% confidence interval) per kWh traded. On a yearly basis the profits per EV would center around €53. It can be concluded that competition has a detrimental effect on the returns for VPP strategies, driving it towards unprofitability.

### 5.2 People: Societal Perspective

In contrast to the diminishing returns under competition for fleet owners there are increasing benefits for consumers of electricity the more fleet owners participate in VPP trading. As fleet owners make additional energy available to the market, the supply increases while demand remains the same, which has the effect that the clearing price decreases. However, when fleet owners charge their EVs for VPP purposes, the demand increases, while supply remains the same, which has an adverse effect on the clearing price.

To investigate the overall effects of this, the prices for electricity are measured in a Power TAC simulation without VPPs of EVs and then the results are compared with a paired t-test to the same simulation, but with VPPs. The comparison suggests that the average wholesale price is significantly lower when VPPs are available. The magnitude of the price difference is a function of the fleet size. At the saturation point of 57%, the price is reduced by on average 3.2%. The 95% confidence interval of a paired t-test for the electricity price reduction is [2.3, 4.2]%. Figure 5 shows the electricity price reduction as a function of the EV penetration. If the price is weighted by the quantity sold per hour the decrease is significant (paired t-test: \(p < 0.01\)). In contrast to this, previous research found a larger reduction of 14% and 14.5% of the energy price (Vytelingum et al., 2011, Ramchurn et al., 2011b). The difference can be explained by car usage. Whereas their batteries are always available for balancing purposes, the batteries in this research are constrained by the trade-off between driving and balancing the grid, which increases the utility for the customer.

Another corollary of this business model is its impact on the electricity price variability. By supplying energy at peak prices and using energy during low prices, electricity tariff volatility is moderated. A two sample F-test for variances comparing the volatility of simulations with and without VPPs yield that variance is significantly reduced (\(p < 0.05\)). We argue that these price effects on the wholesale market are also transferred to the retail market as a decrease in variation reduces the necessity for standby capacity which needs to depreciate its capital cost over short times of operation.

### 5.3 Planet: Greenhouse Gas Emissions

\(CO_2\) as a potent greenhouse gas is a major source of climate change. Climate change is responsible for an increase in the average temperature, a tendency for more extreme weather events, and rising sea levels (IPCC, 2007). Both balancing the grid and increasing the number of EVs, because of their higher efficiency as compared to combustion cars, reduces overall \(CO_2\) emissions. The trading mechanisms described in this paper, which constitute a VPP, reduce \(CO_2\) emissions as will be explained in this section.

---

\(^5\) assuming approximately every second person has a car like for example in The Netherlands or Germany
Carbon emission intensity refers to the average emission rate of carbon for producing energy. We measure it in terms of CO$_2$ per MWh. Previous research asserts that there is a positive relationship between carbon intensity and energy demand. The reason for this is that during peak demand additional energy requirements are met with carbon intensive power plants. The linear nature of this relationship can be captured as follows (Vytelingum et al., 2011):

$$10) \ CI = 0.1075D + 18.125$$

where $CI$ is the carbon intensity in gram of CO$_2$ per MWh, and $D$ is the total demand of the UK market valid for the range of 2250 to 4250 MW.

We previously determined that VPP trading reduces the variance of the electricity price. This suggests that the minimum price increases and the maximum prices decreases. We pair this with the basic economic assumption that price is an indicator for supply: the higher the price the more suppliers are willing to sell. Therefore, the maximum price corresponds with the highest carbon intensity, while the minimum electricity price is associated with the lowest carbon intensity. Now, we determine the impact of VPP trading on CO$_2$ emissions by applying the relationship from equation 10. The corresponding lower confidence interval is 1.2% and the upper confidence level is 3.5% ($\alpha = 0.05$). In other words we are 95% confident that the reduction in CO$_2$ emissions lies between 1.2% and 3.5%. With current worldwide CO$_2$ emissions of 29 million kt that would yield a reduction between 0.35 and 1 million kt of CO$_2$ emissions (Worldbank, 2013). Next to the electricity price decrease also the carbon emission reduction is lower than the 7% from previous research (Vytelingum et al., 2011). The difference can again be explained by the trade-off between driving and balancing the grid in our research.

### 6 Managerial Implications

As fleet owners and car producers are slowly focusing more on EVs they have to be aware of new business models and policies for EVs. We illustrated the effects of a new business model for EVs which offers additional profit streams for EV fleet owners, cheaper electricity prices for consumers, and lower CO$_2$ emissions. Even though this paper is not specifically directed towards a certain fleet owner there are some beneficial recommendations they can draw from our research. A key takeaway is that it is important to be a first mover. The profit per EV decreases with each additional EV on the market. This way an initial scope disadvantage of a relatively small EV fleet can be offset and
valuable market insights can be gained. These insights enable fleet owners and car producers to enter other markets such as retail or ancillary services and ensure critical contracts ahead of competition. By engaging in trading on the wholesale market fleet owners balance the grid and decrease the average electricity price for every consumer. Businesses can use this to position themselves as a socially responsible firm that thinks and acts in the interest of society. Further, energy providers and the DU benefit from trading. They incur less balancing costs with the proposed trading strategy. Fleet owners need to take advantage of this and negotiate contracts with them for possible compensation. Another benefit is a significant CO₂ emission reduction. Lobbying for recognition of these reductions as EU Allowance (EUA), which is a carbon credit for the EU Emissions Trading Scheme (ETS) (European Parliament, Council, 2003), is crucial. These allowances can either be used to offset CO₂ emissions in the fleet owner’s value chain or simply be traded for cash. A final consideration is that this research focuses on a scenario where participants have limited market power and manipulation of the market is prevented by the market operator. However, it is possible that an EV fleet owner does have a sufficient mass to exercise market power, which would result in higher benefits on the profits, but have adverse effects on people and planet. Market operators need to be aware of the omnipresent threat of market manipulation in the electricity sector, and should install counter measures.

7 Conclusion and Future Work

Increasing volatility in energy prices creates room for new business models in the future. This research presented the implications of a business model where fleet owners charge EVs during off peak hours and sell energy back to the grid during peak hours. A crucial factor in the business model is the depreciation cost for batteries over its life cycle. We could demonstrate a favorable impact of VPP trading on the triple bottom line: People, planet, profit. For people evidence suggests that there are welfare gains for society as a whole due to reductions in the average electricity price by about 3.2%. Besides there is proof of a reduction in carbon intensity. This leads to a decrease in CO₂ emissions of on average 2.3%, which has a positive impact on the planet. Depending on the developments in battery technology, fleet owners can make a significant profit with this business model, which, however, decrease with increasing competition. An EV penetration of 57% saturates the market.

In our current model we focus on idle EVs only. For future research it would be interesting to elicit the valuations and preferences of individual consumers for EV availability. They could, for example, decide to postpone trips with the EV if they can make a good arbitrage deal now; an alternative for fleet owners would be to offer service levels for EV availability to segment customers by their flexibility. Another rewarding topic for future research will be VPP as generators in ancillary service auctions for minute reserves. Significantly higher peak prices on the ancillary market are very attractive for VPPs. Also the study of incentive structures and mechanisms of EV storage in micro grids, where power generation, storage, and charging needs to be micromanaged is a promising field of application for VPPs. Individual homes with solar panels or small windmills combined with an EV and other storage capacity could function as a self-sufficient micro grid; or loses could be avoided in solar and wind parks with smart EV charging.

With a positive outlook on the triple bottom line and additional markets at the retail and ancillary services level, the idea of EV VPPs slowly becomes economic reality.

References


