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IS-Centric Business Models for a Sustainable Economy - The Case of Electric Vehicles as Energy Storage

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Abstract. The use of electric vehicles as reasonable alternatives to conventional vehicles with combustion engines will become more attractive in the near future. In addition, the ongoing energy turnaround increases the required amount of regulation reserves to stabilize the power grid. In this paper, we employ an Energy Informatics approach to construct an IS-centric business model to coordinate the charging processes of thousands of electric vehicles and sell this aggregated storage at an energy market. Furthermore, we analyze the effect of various management strategies for the IS artifact. We demonstrate that the business model can yield high revenues by utilizing electric vehicles as distributed storage devices for frequency regulation. This additional revenue stream for vehicle owners further increases the appeal of this sustainable technology.

Keywords: Sustainability, Green IT/IS, Business model, Electric vehicles

1 Introduction

The use of *electric vehicles*[1] (EV) as reasonable alternatives to conventional vehicles with combustion engines will become more attractive in the near future. In recent years, electrified transportation has expanded enormously due to an increasing scarcity of fossil fuels, such as oil, which induces higher prices. The willingness to reduce CO2 emissions as well as millions of government subsidies have made electric mobility more attractive. In addition, the establishment of an extensive charge point infrastructure has raised the sales figure of pure electric vehicles in the United States by more than 500% within a single year (Electric Drive Transportation Association 2013). It is anticipated that approximately one million EVs will drive on the roads of various countries like the USA, Germany, UK, or China by 2020 (The White House 2011; Federal Government of Germany 2009; HM Government 2009). While currently, charging sessions strain the power grid just marginally, handling additional energy demand caused by thousands of charging EVs will become one of the main challenges in the near future (Lopes et al. 2011).

At the same time, incisive events like the nuclear disaster in Fukushima speed up the energy turnaround in many countries. Because of the substantially increased gen-

[1] In the context of this paper, we use electric vehicles for all kinds of purely electrified cars.

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eration through renewable sources like wind and solar power, the power grid has to deal with very volatile amounts of electricity during the course of a day. Because renewable energies depend on exogenous environmental circumstances, the power grid has to adjust to sudden supply shocks if, for instance, the weather changes in an unanticipated way. These supply shocks cause the grid frequency to deviate from its balanced state of 50 Hz. Therefore, *frequency regulation* (FR), which already is an important continuous process to stabilize the electrical power grid by using additional energy reserves, will increase in relevance. While minor frequency disturbances can be compensated by small adjustments in power plants, large deviations have to be corrected using special resources. This process needs to be executed in both directions. To rebalance increased frequencies the overall energy demand has to be increased or the power supply must be reduced (negative regulation). On the other hand, to balance the power grid during a decreased frequency level, energy consumption has to be reduced or supply has to be increased by feeding in additional energy reserves (positive regulation).

Thinking about the aforementioned changes in the transportation and energy sector leads us to the following questions, which drives the subsequent research: Is it possible to combine these changes in order to establish a profitable business? Since electric cars store electricity, these vehicles are naturally distributed storage devices and can be used for frequency regulation. In fact, a bi-directional energy transfer enables the option to draw current during increased frequencies and provide electricity to the grid at decreased frequencies (Hinkle et al. 2011). This technology is called *vehicle-to-grid* (V2G). While a single EV only has a marginal effect on the power grid, an aggregation of a reasonable amount of vehicles must be achieved to participate in the regulation market.

In this paper, we introduce a business model for the coordinated aggregation of EVs as distributed storage devices to enter the market for frequency regulation. Thereby, we bridge the gap between adequate charging of EVs, while at the same time generating revenue from providing grid regulation. We apply known scheduling strategies to the new problem of coordinated charging of electric vehicles. This procedure is classified as “Exaptation” of the Knowledge Contribution Framework of Shirley and Alan (2013), while the business model itself directly contribute to the emerging IS research field of Energy Informatics as introduced by Watson et al. (2010).

The core of our business model consists of an information system, illustrated in Figure 1, that acquires and analyzes data on the usage of EVs on the one hand and the regulation market behavior on the other hand. It processes this data subject to constraints posed by the physical system and employs management strategies to derive charging strategies that attempt to maximize revenues. For evaluation of the business model, we use more than 34 million privately used EV data points including, for instance, GPS coordinates and *state of charge* (SoC) values to construct a realistic environment. The data was collected and evaluated in cooperation with an industry partner. Furthermore, we assess the profitability of the business model within the *German Control Reserve Market* (GCRM). We use historical data regarding the actual required energy demands and the paid regulation prices from 2012, accessed from Vattenfall Europe Information Services (2013). Eventually, we are able to show the current potential and benefits from aggregating EVs for frequency regulation to the owners of the vehicles, as well as the operator of the business model. Thereby, we show that IS research as a whole can provide major contributions towards the application of known technologies to new problems.

Hence, this paper investigates the following research questions:

- How can IS support a business model for the utilization of electric vehicles as distributed storage devices in the energy market?
- To what extent can different management strategies for vehicle charging increase the revenues of this business model?
- What revenues can be generated for the vehicle owners and what are the incentives to participate in this business model?

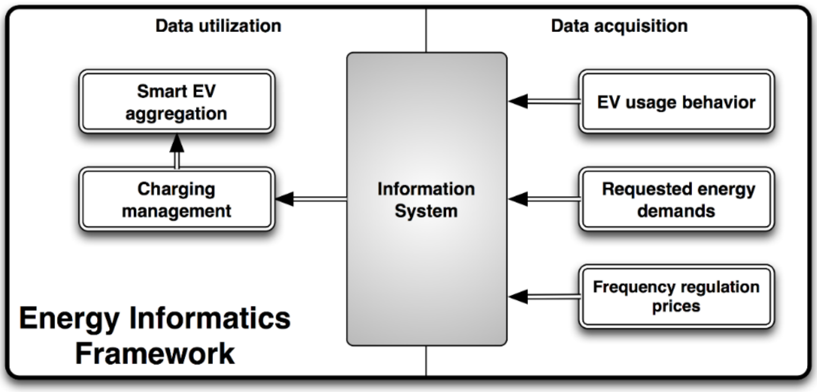

Fig. 1. Positioning of the Information Framework in the Energy Market

The paper is structured as follows. The next section presents an overview of past research directly related to this paper. Afterwards, we define the business model and the mathematical description of core information system. This is followed by an introduction of various strategies to charge EVs concurrently, taking into account different user and grid related constraints. Afterwards, we determine simulation settings containing model constraints, EV properties, and customer agreements that have to be fulfilled by the management strategy. This is followed by a presentation of our simulation results, which also allow inferences on the profitability and feasibility of this approach for the near future. Finally, we conclude this paper and provide an outlook on our upcoming research.

2 Related Work

The contribution of IS research towards a sustainable energy paradigm has become more pronounced in recent years. Particularly Watson et al. (2010) have drawn attention to applying IS techniques to increase energy efficiency and to develop sustainable IT-centered business models. Employing skills from Computer Science, Electrical

Engineering, and certainly Information Systems Energy Informatics links different research fields to investigate a topic of enormous relevance to society. Kossahl et al. (2012) analyze the domain of Energy Informatics and present an overview of existing literature and research agendas for IS and business studies. They find that particularly the potential of electric mobility still needs to be addressed employing the toolbox of IS research. Corbett (2011) emphasizes the importance of communication technology and information systems and argues that this will play a central role in the realization of smart grids, in which electrical infrastructure is supported by information and communication technology. In [Removed] we have already analyzed the technical and market related requirements to use EVs to participate in the frequency regulation market, which form the core of the IS-centric business model presented in this paper.

In addition to IS research, scholars of other disciplines have investigated the potential of EVs for ancillary services, such as frequency control, as well. One of the first pilot projects trying to apply such an approach was realized by Brooks (2002) who finds that EVs are well suited for frequency regulation, because of their short ramp-up time in contrast to conventional regulation sources. Depending on individual driving activities, annual gross revenues from $ 1,000 to $ 5,000 can be achieved. Furthermore, Kempton and Tomić (2005a, 2005b) compare different energy markets and formulate fundamentals to calculate revenues from using EVs for regulation purposes. They argue that vehicles are parked during 96% of the day. Thereby, EVs are able to generate annual revenues of $ 2,554 per vehicle from frequency regulation. However, the high volatility of regulation energy prices is not addressed in their research. Kamboj et al. (2011) estimate revenues of $ 1,200 to $ 2,400 per year, assuming a vehicle participation of 15 hours a day and a regulation price twice as high as normal. However, in all of the above publications there are no charging management strategies applied to maximize revenues. We argue that this is one of the main flaws in assessing the results from previous studies on the use of EVs for frequency regulation.

Research on the coordination of charging processes of EVs has been discussed quite extensively (Flath et al. 2013; Schuller et al. 2012; Su and Chow 2012; Sundstroem and Binding 2012), but without reference to a particular business model. To fulfill power grid constraints even with a high penetration of EVs, Han et al. (2012) proposes two management approaches that optimize charging schedules and charging rates. Additionally, to consider deterministic arrival, departure, and charging characteristics, Chen et al. (2012a; 2012b) formulate a deadline-scheduling problem for EVs. A utility based pricing scheme was simulated with Earliest-Deadline-First and First-Come-First-Served strategies to fulfill customers' requirements. Furthermore, Flath et al. (2012a) formalize the coordination of charging processes as a minimum revenue management problem and simulate this approach within a stochastic setup. In a further research, Flath et al. (2012b) formulate different charging strategies according to their requirements about future price and upcoming trip information. Their evaluation shows that even with low information requirements, individual energy costs can be reduced by using charging strategies. They also found that for charging management accurate trip information is more important than electricity price forecasts. Furthermore, Sanchez-Martin and Sanchez (2011) focus on optimal charging management for EVs and Plug-in Hybrid Electric Vehicles at parking facilities.

Unfortunately, in almost all publications, business models are neither based on real data nor evaluated with real market prices for frequency regulation. Therefore, the calculated revenues of the aforementioned research fluctuate from 34 Euros to several thousands. Hence, one of our main contributions is to perform a simulation based on an adequate benchmark set for both EV usage behavior and regulation prices, utilizing a comprehensive information system for charging management.

3 Business Model

3.1 Model Architecture

In the following section, we introduce a model including an information system, which is responsible for decision making illustrated by Figure 2. The model is based on the assumption that each vehicle participates in the V2G regulation program, once it enters a parking lot in the parking facility. As an incentive, the vehicle owner will be rewarded with cheap electrical energy. A parking facility has the necessary billing infrastructure already in place, which only needs to be adapted. The IS-operator offers the aggregated energy reserves at the regulation market (1). The market operator may purchase the offered control reserves as an option. If this energy is requested to stabilize the power grid after a frequency disturbance, the aggregator uses the connected vehicles to provide regulation (2). At this point, the *charging control unit* (CCU) selects a reasonable number of EVs, depending on strategy and customer constraints (3). Assuming that the current EV reserves are not sufficient, conventional control reserves can be used in addition to support the regulation process (3). Although this possibility is considered by the model architecture, we will not go into further details for brevity. Finally, the aggregator is paid for the provided regulation service by the energy market (4).

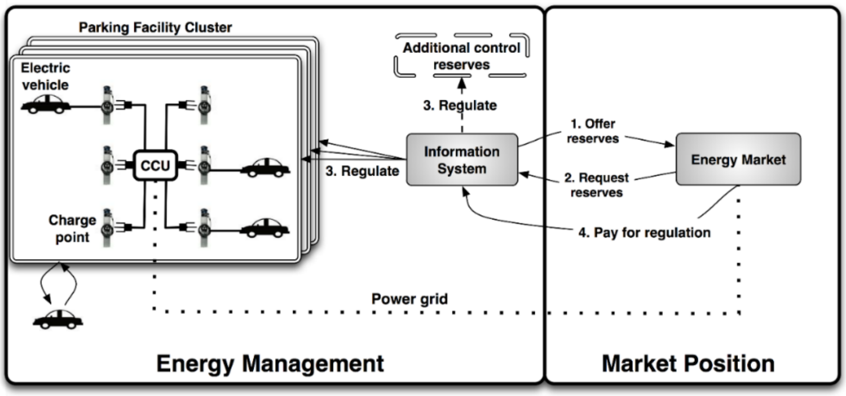

Fig. 2. Business model architecture

In the further course of this paper we will focus primarily on step 3 and 4, the acquisition of energy and the generation of an optimal revenue through EVs, because the market position is already described in detail by [Removed]. More importantly, bringing up enough energy to participate at the GCRM, while fulfilling customer charging requests, is an essential requirement for deriving a feasible business model.

3.2 Mathematical Description

The IS-operator has to react immediately to current grid conditions, once the offered control reserves are requested by the energy market. As mentioned above, a single instance, the charging control unit, monitors the charging process of each vehicle on the one hand and decides which EVs are used for regulation on the other hand (see Figure 2). Hence, the CCU is also responsible for the power management of the parking facilities by economically providing power to parked vehicles. In order to operate each EV separately, the CCU sends a signal to the respective CPs within its network. To formulate such a coordination scheme, we define each CP as a 5-tuple $(\sum, S, s_0, \delta, F)$, with

$$\begin{aligned} &\Sigma = \{i_0, i_1, i_2, i_3, i_4\}, \\ &S = \{s0_{idle}, s1_{charge}, s2_{reg-up}, s3_{reg-down}, s4_{drive}\}, \\ &s_0 = s0_{idle}, \\ &\delta : S \times \Sigma \to S, \\ &F = \{s4_{drive}\}. \end{aligned} \quad (1)$$

Vehicles will be initialized with $s0_{idle}$, the idle state, and finish the parking session in the final state $s4_{drive}$. Depending on the coordination by the CCU, an EV will be set to the charge state $s1_{charge}$ or to one of the regulation states $s2_{reg-up}$, $s3_{reg-down}$, if frequency regulation is required. By applying the state transition function δ, the CP changes its current state to the next state with respect to the input signal $i \in \Sigma$. Further, we define an electric vehicle E_k as the following 4-tuple

$$E_k = \{E_{cap}, E_{Soc}, E_{pTime}, E_{pDur}\}, \quad (2)$$

with a constant capacity E_{cap}, an initial state of charge E_{SoC}, a start time value E_{pTime} and a parking duration value E_{pDur}.

For each state the model calculates an individual revenue depending on the state duration, CP power, price for providing regulation, and price for the charged electricity. Hence, depending on a current state $s_i \in S$, at a specific time t_j, the regulation algorithm calculates for each vehicle E_k, the corresponding revenue $R(s_i, t_j, E_k)$, as follows

$$R(s0_{idle}, t_j, E_k) = 0, \quad (3)$$

$$R(s1_{charge}, t_j, E_k) = 0, \quad (4)$$

$$R(s2_{reg-up}, t_j, E_k) = \begin{cases} 2 \cdot \int_{t0}^{t1} (CP_P(t) \cdot p_r)\, dt, & \text{if } \mathrm{s}_{t-1} = s1_{charge} \\ \int_{t0}^{t1} (CP_P(t) \cdot p_r)\, dt, & \text{otherwise} \end{cases} \quad (5)$$

$$R(s3_{reg-down}, t_j, E_k) = \int_{t0}^{t1} \big(CP_P(t) \cdot (p_r + p_e)\big)\, dt, \quad (6)$$

with $CP_P(t)$ as the actual CP power at t between the start, t_0, and the end, t_1, of the respective state duration. In Equation 5 and 6 the revenue is determined by p_r for a given positive or negative regulation price on the one hand and p_e representing the normal electricity price on the other hand. Since Equation 6 defines the negative regulation state, the IS-operator is able to achieve revenue from both the vehicle owner for charged electricity and the energy market for regulate the grid frequency. To calculate the total revenue for a sequence of state transitions, the following recursive function is applied

$$R(s_j, t_j, E_k) = \begin{cases} R(s_{i-1}, t_{j-1}, E_k) + 0, \\ R(s_{i-1}, t_{j-1}, E_k) + R(s2_{reg-up}, t_j, E_k), \\ R(s_{i-1}, t_{j-1}, E_k) + R(s3_{reg-down}, t_j, E_k), \\ R(s_{i-1}, t_{j-1}, E_k) + 0, \end{cases} \tag{7}$$

using an initial timespan $t_0, \ldots, t_m$ with $t_0 = E_{k,pTime}$ and $t_m = E_{k,pTime} + E_{k,pDur}$, an initial revenue of $R(s_0, t_0, E_k) = 0$ and a final revenue of $R(s4_{drive}, t_m, E_k) = 0$. Starting at $i, j = 1$, while s_0 is the initial state, according to Definition 1.

Hence, we are able to translate each parking session into a sequence of state transitions and, thus, calculate for each state the corresponding revenue. According to the above recursive function, the last state determines the total revenue of the parking session. However, the forecast of future events is limited and past decisions regarding the next state cannot be reversed in reality. Thus, finding a sequence of state transitions to determine the maximum possible revenue is a major challenge. In reality, a precise forecast depends on various environmental conditions and is not achievable in an appropriate manner. Nonetheless, an accurate forecast regarding frequency deviations is only important for the positive regulation case. This is because discharging EVs to free more capacity, while there is no need for regulation, is not practicable in any case. Due to various uncertainties like the rather stochastic behavior of frequency deviations on the one hand and uncertainties in accurate parking duration and driving behavior forecasts on the other hand (Goebel and Voß 2012; Feixiang et al. 2011), it is hardly possible to find an optimal sequence of state transitions.

4 Electric Vehicles Charging Strategies

In this section, we introduce different management strategies to coordinate the charging process of EVs concurrently. Each of the following strategies preferred different vehicles based on their current properties. All properties were calculated based on real data. We collected for example GPS coordinates and the battery state of charge of real electric vehicles in a fine granulated manner (minutely basis). We determine a specific schedule that handles existing energy resources, while taking into account the charging urgency of certain EVs. All strategies are commonly known in disciplines like computer science to schedule different processes and are now applied to a new problem. In terms of costs, we will not consider any investment costs, since they do not differ across the subsequent strategies. While they must be considered when assessing the overall profitability of the business model, this is not necessary when comparing different charging strategies regarding pure revenue. Operational costs, such as charge point maintenance and battery degradation, are likely close to constant across charging strategies, as well. Furthermore, costs, such as battery degradation, depend on factors like the type of the battery, temperature, or the current of the charging process itself.

Figure 3 illustrates the need of charging strategies under certain conditions using a simple example. We see eight EVs with different state of charges and parking durations. All of these vehicles are connected to the grid and request energy from the parking facility. However, we assume that the operator is only able to provide full power to four of these EVs at the same time. The reason why it is quite likely to need a prioritization of charging requests in the near future is that once several thousand EVs attempt to charge concurrently, the current power grid is not able to provide such sudden spike of energy demand. Thus, to prevent a breakdown the power outlet of each parking facility in our framework is limited. Considering driving requirements, the empty EVs should be charged first. However, considering to the IS-operator's total revenue, EVs with low batteries cannot be used for positive regulation. Parking time is another critical instance because if a long parking duration is given, the EV charging request can be shifted to a later point. Furthermore, EVs will be implicitly prepared for upcoming frequency disturbances, depending on the charging management strategy.

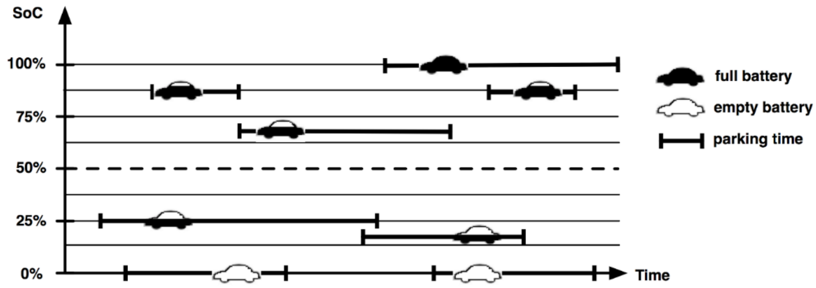

Fig. 3. Charging management example

One of the simplest ways to manage charging requests is *first-come-first-served* (FCFS). In this strategy, EVs will be charged in the order in which they enter the parking facility. Hence, the only vehicle property which determines the *charging order* (CO) of a number of EVs is the start time value p_{Time}. We define the CO as follows

$$CO_{FCFS} = E_{1,pTime} < E_{2,pTime} < \cdots < E_{n,pTime} \quad (8)$$

The parking facility enables energy transfers for requesting CPs as soon as the maximum power utilization is reached. The CCU stores all remaining charging requests in a queue and handles them gradually, once a sufficient amount of resources is available again. Since FCFS does not consider any other vehicle properties like the state of charge, we use this strategy as a baseline to compare the subsequent strategies.

The *earliest-deadline-first* (EDF) management considers the duration of each parking session. In this strategy, the charging request of vehicles with short time constraints are enabled first. Thus, the departure times of customers are considered for scheduling. Therefore, the algorithm uses the parking duration property p_{Dur} to decide which EVs will be charged. The main advantage of this strategy is the prioritization based on the customers time constraints. Note that because short charging sessions are preferred, EDF results in high frequently changes. Vehicles with long parking times will be shift to a later point. The charging order using EDF is determined by the property E_{pDur} as

$$CO_{EDF} = E1_{pDur} < E2_{pDur} < \cdots < En_{pDur}. \quad (9)$$

The *lowest-SoC-first* (LSoCF) management is the first strategy that considers the battery status of each vehicle. The charging order is determined by the SoC values in such a way that the EV with the lowest battery will be charged first. This strategy is very reasonable regarding the importance of driving purpose for the vehicle owner, since EVs with very low batteries have to be charged in order to leave the parking facility again. In contrast to EDF charging, this strategy entails low frequently changes, due to preference of low batteries, which in turn results in long charging activities. The charging order CO using LSoCF is determined by the property E_{SoC} as follows

$$CO_{LSoCF} = E1_{SoC} < E2_{SoC} < \cdots < En_{SoC}. \quad (10)$$

The *highest-SoC-first* (HSoCF) strategy is the counterpart to the abovementioned LSoCF strategy. This charging management considers high battery status of customers EVs and prioritizes based on the SoC value. Similar to EDF the frequency of changes will be quite high, due to short charging durations on average. This scheduling procedure may not be reasonable for vehicle owners, due to the deprivation of EV with low batteries. However, the main advantage of this charging management is that more positive regulation resources will be available in contrast to any other strategy. This is because EVs with low battery capacity cannot be used for positive regulation considering customers driving requirements. In simple terms, if the battery is low on reserves, a vehicle owner would not offer the remaining energy to the market; otherwise the vehicle would not be able to leave the parking lot. The charging order CO using HSoCF is determined by the property E_{SoC} as follows

$$CO_{HSoCF} = E1_{SoC} > E2_{SoC} > \cdots > En_{SoC}. \quad (11)$$

5 Electric Vehicle Properties and Constraints

5.1 Capacity $\boldsymbol{E_{cap}}$

The maximum capacity of each EV is given by E_{cap} and depends on the vehicle type. Table 1 shows the different types we use within the simulation based on probability distributions. The selection was chosen in a way that the differences of the individual capacities differ substantially. Moreover, these vehicle types are already in series production and the model can be freely adjusted to current or future conditions. Since other vehicles on the market differ only slightly with respect to capacity, the simulation output would change only marginally using a larger selection of EV types.

Table 1. Vehicle Types		
Type	Capacity cap (kWh)	Probability (%)
Mitsubishi i-MiEV[2]	16	35
Nissan Leaf[3]	24	35
Mini E[4]	35	29
Tesla Roadster[5]	56	1

5.2 State of Charge E_{SoC}

The initial state of charge value E_{SoC} declares the current battery capacity, once the vehicle has entered a parking lot. In order to derive a probability distribution for the simulation, we determine the SoC values based on a histogram obtained from our data set. Figure 4 shows the calculated distribution for a quantity of 40,000 EVs. As we can see, the distribution shows an increased probability for a SoC > 50%. This results from the evaluation of the data points regarding EV usage behavior. Thus, the EVs in the simulation have E_{SoC} values between 50% and 90% with particularly high probabilities.

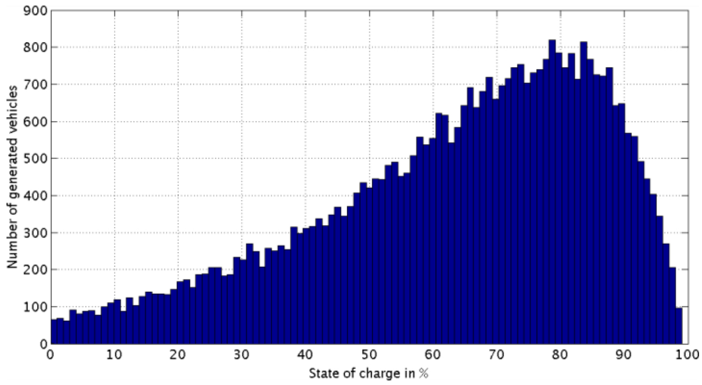

Fig. 4. Initial state of charge distribution

5.3 Parking Time E_{pTime}

The parking time E_{pTime} of each vehicle defines the initial starting time at which the customer connects the EV to the grid. Hence, this value also determines the occu-

[2] http://www.imiev.de/docs/iMiEV-daten.pdf, accessed 8 August 2014.
[3] http://www.nissanusa.com/electric-cars/leaf/versions-specs/, accessed 8 August 2014.
[4] http://www.mini.co.uk/about-us/miniefficiency/mini-e/, accessed 8 August 2014.
[5] http://www.teslamotors.com/en_AU/roadster/technology/battery, accessed 8 August 2014.

pancy rate of the parking facilities. To make the simulation as realistic as possible we used 37 different occupancy rates of urban parking facilities in Germany with more than 15,000 parking lots in total. Figure 5 illustrates two frequently used parking facilities in Frankfurt. Both figures show an almost normally distributed occupancy rate between 8 a.m. to 20 p.m., although the location as well as the overall number of parking lots differs.

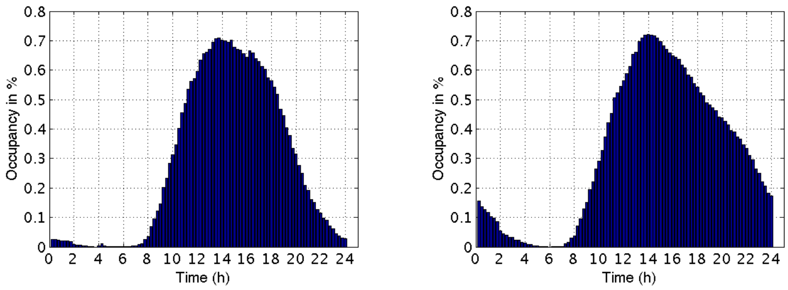

Fig. 5. Occupancy rates of two frequently used parking facilities in Frankfurt

5.4 Parking Duration $\boldsymbol{E_{pDur}}$

The parking duration E_{pDur} is the vehicle property, which declares the parking time during the simulation process. This value depends on many different user and facility related conditions. For example, the average parking duration at a central station is quite low, because central stations are typically characterized by arriving and departing passengers and, thus, show a high vehicle fluctuation on average. In contrast to that, parking lots located near malls are mainly used for shopping which leads to an increased parking duration. Hence, the purpose of parking and the location of the parking lot are two main factors influencing the EV property E_{pDur}. As we are only able to estimate the exact parking duration based on the calculated occupancy rates and E_{pDur} depends on various user, environmental, as well as time related factors, we use a Chi-square distribution, illustrated by Figure 6. The distribution characterizes a frequently used parking facility with parking durations between 20 and 60 minutes. However, parking durations above 2h are also possible according to this distribution. Both the average and the maximum values depend on the chosen degree of freedom (DF). The DF allows to increase the overall parking duration and respectively the vehicle fluctuation rate within the simulated parking facility. Note that an increased DF also results in an increased participation time in the V2G regulation approach.

Finally, we are able to generate a predefined number of EVs based on the above properties. For example an EV created during simulation could have the properties $EV_1 = \left[\mathrm{EV_{cap}} = 24\mathrm{kWh}, \mathrm{EV_{SoC}} = 76\%, \mathrm{EV_{pTime}} = 1{:}15\ \mathrm{p.m.}, \mathrm{EV_{pDur}} = 56\mathrm{min}\right]$. As we can see, the maximum capacity of EV_1 is 24kWh, thus, the generated vehicle is a Nissan Leaf. The initial SoC is 76% and the vehicle enters the parking facility at

1:15 p.m. The total parking duration is 56 minutes; hence, the IS-operator obtains an additional resource between 1:15 p.m. and 2:11 p.m. to regulate the power grid.

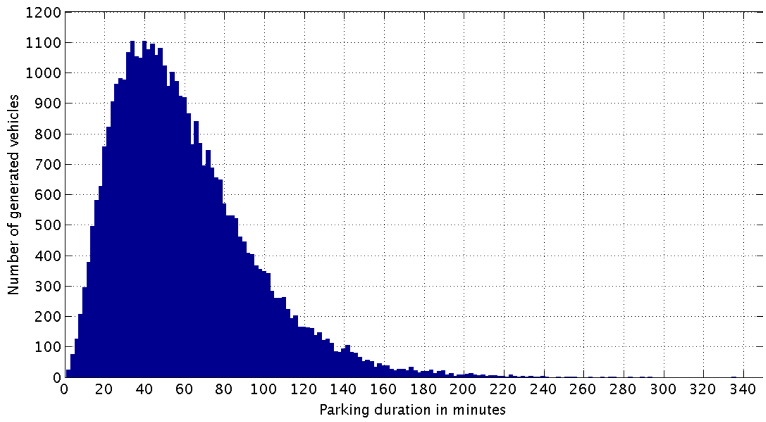

Fig. 6. Initial parking duration distribution

6 Simulation Results

We simulated the introduced business model within the German Control Reserves Market to achieve a realistic scenario regarding timespan, duration, and magnitude of grid frequency deviations. Once a disturbance occurs and the energy market requested control reserves to balance the power grid, we determine the actual paid regulation price based on historical data. Thereafter, the algorithm calculates the revenue for the business operator based on the available regulation resources. Each EV within the parking facility will be considered with respect to the introduced management strategies.

Table 2 provides the simulation outcome concerning the total revenue as well as the maximum and average revenue per vehicle and day, respectively year. Two different levels of charging power – 3.6kw and 25kw – were used, while the highest revenues for 25kw charging is highlighted in green. As we can see, the highest revenue for the business operator can be achieved by applying HSoCF. This charging management is approximately 20% higher than LSoCF, which provides the lowest total revenue (positive regulation). Such a result is caused by the fact that in contrast to other strategies most of the charged electricity can be used for positive regulation. The simulation also shows that charging management has just a negligible influence on negative regulation revenues. This is because we do not assume any restrictions in charging EVs batteries, since a vehicle owner would not complain about obtaining electricity. Hence, in contrast to positive regulation amounts the overall revenue of negative regulation always remains the same no matter which charging management is selected. Concerning the individual EV revenues per day and year, the best results are obtained by the LSoCF strategy. If we look at the baseline strategy FCFS, participating customers are able to obtain approximately € 0.66 to € 35 for negative and € 3.75 to € 104 for positive regulation on a daily base. The standard deviations (SD) are € 0.79 to € 4.53 for negative and € 3.36 to € 11.63 for positive regulation. The high variations largely depend on the day, parking time, duration, and initial SoC values of the EVs as well as on the rarity of frequency disturbances itself. Furthermore, a maximum annual gross revenue per EV of approximately € 1,081 for negative and € 2,970 for positive regulation is calculated. These results confirm rougher estimates of previous studies (Brooks 2002, Kempton and Tomić 2005a, 2005b, Kamboj et al. 2011). The high deviations between average and maximum revenues are caused by the fluctuating occurrence of frequency deviations. Therefore, the requested amounts of control reserves and, thus, the prices for providing regulation strongly differ. We found that FR shows a rather stochastic behavior including extraordinary peaks in both directions. As a result, the major revenues are generated only on a few days, while also the revenues of customer's EVs substantially depend on the time and date vehicles are connected to the grid.

The simulation results can serve as an incentive to buy electrified cars and to increase the sales figures of EVs. The model presented in this paper also provides an opportunity for new businesses to offer EV reserves within a micro energy market. This in turn opens a possibility for EV owners to offer their energy reserves in this micro market and to eventually generate revenues with parked cars. On the other hand, such a model is able to aggregate a large amount of regulation resources to secure the power grid. Particularly during times of a rapidly progressive energy turnaround, due to the integration of a large number of renewables like wind and solar power, the provision of a reasonable amount of control reserves is one of the main challenges faced today. The business model introduced in this paper not only enables an opportunity to integrate EVs into the power grid, but also opens an option to aggregate a large amount of energy to stabilize the grid.

Table 2. Simulation results of each charging management strategy

FCFS		**EDF**		**LSoCF**		**HSoCF**	
Neg.	Pos.	Neg.	Pos.	Neg.	Pos.	Neg.	Pos.
Total revenue per EV and year (25kw first row; 3.6kw second row)							
14.66k	36.82k	15.35k	39.88k	15.29k	34.21k	14.86k	42.85
8,770	17.70k	8,406	17.9k	8,285	17.96k	8,421	18.08
Maximum revenue per EV and year (25kw first row; 3.6kw second row)							
1,081	2,970	1,145	3,112	1,146	2,537	1,105	3,934
627.88	2,189	656.56	2,312	602.43	2,404	669.46	2,308
Average revenue per EV and year (25kw first row; 3.6kw second row)							
186.85	787.73	203.03	753.25	197.05	822.52	184.54	681.
64.45	136.66	63.48	142.14	62.68	139.52	66.03	139.
Maximum revenue per EV and day (25kw first row; 3.6kw second row)							
35.18	103.97	31.64	93.75	36.75	112.5	20.47	88.7
10.8	35.53	12.87	29.60	13.85	32.76	16.20	21.60
Average revenue per EV and day (25kw first row; 3.6kw second row)							

0.66	3.75	0.72	3.50	0.69	4.11	0.66	3.20
0.22	0.58	0.22	0.58	0.21	0.59	0.23	0.59

7 Conclusion

In this paper, we have presented a business model to monitor charging processes of thousands of electric vehicles, while achieving high revenues by utilizing EVs as distributed storages for frequency regulation. We collected and analyzed millions of data points regarding the usage of EVs to derive realistic assumptions for our simulation. We evaluated our business model within a real energy market using millions of historical data points concerning the amount of requested reserves and the prices paid for providing regulation.

By applying different management strategies, we are able to show increasing benefits for the vehicle owners and the business operator. Both operator and customer incentives were analyzed to find an adequate compromise between regulation outcome and vehicle workload. It turns out that the HSoCF strategy generates the highest revenue for the business operator, which is up to approximately 20% higher than LSoCF, the strategy with the lowest revenue in total. We can see that there is a crucial difference in revenues among all strategies considering positive regulation. Considering the vehicle owner's driving requirements, preferring charging requests of EVs with high state of charges is not practicable in any case. In addition, customer revenues for vehicle per day or year are rather average, in contrast to the other strategies. Nevertheless, the highest customer related revenues on average would be achieved by applying the LSoCF strategy. With an outcome of approximately € 0.69 for negative and € 4.11 for positive regulation per day, the participation is quite profitable for EV owners. Although, we outlined the outcomes for different charging strategies independently from costs, our simulation shows the theoretical potential of EVs participating in the energy market.

A total outcome of more than one thousand euro per year for providing negative frequency regulation can be used for business strategies to increase the sales figures of EVs. However, our analysis shows that most of the revenue was generated only on a few days in the course of the year. This is because frequency regulation is a process characterized by major peaks and only at these peak-times prices for regulation are extraordinary high. Furthermore, strong frequency disturbances occur in both directions, thereby enabling revenues of up to € 1.50 per kWh, not only by providing electricity to the grid, but also by drawing electricity from the grid to the EV.

In our future research we will include costs into our consideration to develop a comprehensive business model. Such costs include increased battery degradation, as well as investment and maintenance costs of the CP infrastructure. Furthermore, we will explore charging management strategies that combine elements of those presented in this paper and investigate their revenue effects.

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