Research Center
Finance & Information Management

Fraunhofer
FIT

Project Group
Business & Information
Systems Engineering

Discussion Paper

The Value of Information Exchange in Electric Vehicle Charging

by

Gilbert Fridgen, Philipp Mette, Markus Thimmel

in: Proceedings of the 35th International Conference on Information System (ICIS), Auckland, New Zealand, December 2014

WI-416

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: F.-v.-Schiller-Str. 2a, 95444 Bayreuth
Phone: +49 921 55-4710 (Fax: -844710)

The Value of Information Exchange in Electric Vehicle Charging

Completed Research Paper

Fridgen, Gilbert
FIM Research Center, University of Bayreuth
Friedrich-von-Schiller-Str. 2a
95444 Bayreuth, Germany
gilbert.fridgen@fim-rc.de

Mette, Philipp
FIM Research Center, University of Augsburg
Universitaetsstraße 12
86159 Augsburg, Germany
philipp.mette@fim-rc.de

Thimmel, Markus
FIM Research Center, University of Augsburg
Universitaetsstraße 12
86159 Augsburg, Germany
markus.thimmel@fim-rc.de

EUROPEAN UNION
Investing in your future
European Regional Development Fund

Abstract

Renewable energy integration is accompanied by highly volatile energy generation, which urges energy suppliers to use costly countermeasures to prevent energy imbalances, grid instabilities and power outages. Therefore, using demand-side approaches to shift flexible demand over time is a promising opportunity. In the case of electric vehicles, research papers mostly discuss vehicle drivers' individual charging strategies based upon pricing information. The objective of this paper is to quantify the aggregate economic benefit of an advanced metering approach wherein electric vehicle drivers simply provide information about the start of the next trip to the energy supplier, who can then optimize the charging strategy for all drivers based on this information. By using a quantitative model and a multi-agent simulation for evaluation, we analyze original data from Germany to conclude that advanced metering can enable significant savings. Finally, we present a pricing scheme that would incentivize the drivers to provide truthful information.

Keywords:

Charging strategy, information value, electric vehicle, demand-side management, residual load

Introduction

Climate change and energy security are considered to be among the most pressing issues the world currently faces (Traut et al. 2012). Governments are imposing obligations on industry companies to increase energy efficiency and reduce emissions in order to achieve ambitious climate and energy goals. The energy turnaround, i.e. the substitution of conventional energies, like coal and nuclear, by renewable energy sources, like wind and solar, will lead to a "substantial transformation of electricity systems" (Römer et al. 2012). Germany is at the forefront of the development of energy systems, and plans to shut down all nuclear power plants before 2022 (Economist 2011). However, as wind and sunlight fluctuate over time, energy generation with those sources can be highly volatile (Subramanian et al. 2012). Since the energy demand is also volatile, energy suppliers increasingly face the challenge of grid imbalances, which is, surplus of energy generation or demand (dena 2012). The exact balance between generation and demand is a complex challenge in and of itself (Mattern et al. 2010), and will, according to Christian (2010), become "one of the most critical issues in the transition to less carbon-emitting energy supply systems within the next decades". Nowadays, energy suppliers match energy generation and demand by buying operating reserve and turning large generators on and off. As a consequence, efficiency loss and high opportunity cost lead to payouts for the energy supplier and, eventually, higher energy prices for customers. Moreover, energy storage facilities (ESFs) are used, which are extremely costly and (mostly) too sluggish to absorb energy surplus, especially surplus occurring on the short-term. The issue of efficient and affordable ESFs is considered one of the biggest economic challenges of the energy turnaround. Since the proportion of the renewables increases, the efforts to compensate grid imbalances by adjusting the energy generation ascends. As a result, modern approaches to demand-side management are being developed, with a focus on shifting energy demand to match fluctuating generation (Strbac 2008). According to Flath et al. (2012a), demand-side management approaches "can reduce investments in the grid and the cost of generation (Strbac 2008) while customers can expect savings in their electricity bill (Albadi and El-Saadany 2008)".

Electric vehicles (EV) can potentially serve as compensatory energy storage units, which may help to remedy the problem. Since the parking times of EVs are often longer than the actual charging times, the charging of EVs is temporally flexible. EV charging can therefore be optimized in order to compensate grid imbalances. From an information management perspective, the problem at hand stems from asymmetric information: energy suppliers have no information about the time and duration that an EV is available for charging. When combined with conflicting interests, asymmetric information "can lead to suboptimal allocation of resources" (Copeland et al. 2005) and welfare losses. Existing research articles develop charging strategies mostly on the basis of energy price information, (e.g. Sundström and Binding (2010), Römer et al. (2012), Lopes et al. (2009), Schuller et al. (2012)), and assume that the customers' charging strategies will respond to price signals. However, given the comparatively low cost of the power necessary to fully charge an electric vehicle, (approx. 5 € in today's prices) it is unlikely that customers will be willing to bother with complex pricing mechanisms that yield results which cannot be known in advance.

To this account, information and communications technology (ICT) has already developed an infrastructure which enables EV drivers to dispose of asymmetric information. Through the use of an advanced meter, the energy supplier receives information about the actual driving behavior from the driver. For example, the Chevrolet Volt already comes with a mobile app called Onstar Remotelink, which allows EV drivers to specify charging times and charging modes (General Motors 2011), such as grid-friendly charging. The energy supplier can then determine a charging schedule for each EV, allowing the energy supplier to leverage the flexibility of energy demand (Goebel 2012). Hence, the signaling effect of information exchange can counteract asymmetric information and welfare loss.

Therefore the research question of this paper is defined as follows: How large is the aggregated economic benefit of an advanced metering approach where EV drivers provide information about the start of the next trip to the energy supplier? To investigate this research question, we implemented a simulation based approach for the quantification of the benefits of a smart charging strategy. Moreover, we present a pricing scheme that incentivizes drivers to provide truthful information to the supplier. We will show that advanced metering is able to counteract the welfare loss that occurs as a result of asymmetric information. Therefore, our model simplifies the energy supply side. In other words, we do not differentiate between energy supply and grid operators, do not assume the perspective of any one specific energy supplier, and do not model market competition or energy trading opportunities. This is reasonable, since energy trading does not solve the challenge of surplus of energy generation or demand, but rather shifts it to a higher level: selling surplus energy might solve the problem for an individual energy supplier, but on a national or even international level energy must still be stored. Moreover, transporting energy over large distances (e.g., for exports) leads to energy loss and should therefore also be avoided. Hence, from an aggregate economic perspective, a market view is not necessary, since the energy market only serves to incentivize and distribute the benefits that we have identified. We thus claim to determine the aggregate economic benefit of information exchange by means of an overall hypothetical amount of savings for the value of information in EV charging.

In the next section, we give an overview of existing literature related to our work. Section 3 offers an explanation regarding the focused challenge of renewable energy integration. Section 4 introduces the model, and section 5 presents the data we used for our analysis. Afterwards, we discuss a possible pricing scheme to leverage the economic potential of ICT-based information exchange. Subsequently, conclusions from the model and the simulation are drawn and summed up. We close with a brief summary, discuss limitations of the article and present an outlook on future research.

Related work

Market penetration of EV faces several obstacles, including long charging times and shorter driving range of EVs, as well as skepticism among potential users (Tate et al. 2008). Thus, business models to counteract these obstacles are being developed. Kley et al. (2011) present several business models for electric mobility, and provide decision support for various stakeholders. Among these, a promising approach is using EVs to shift the load into off-peak periods, which has already been discussed since 1983 (Heydt 1983). According to Kempton and Tomić (2005b), vehicles are parked, on average, for 96% of the day. Existing research papers propose load-shifting with specific charging strategies, such as a decentralized approach (Qian et al. 2011), coordination based on local grid parameters (Lopes et al. 2010), or a central optimal planning authority (Clement et al. 2009; Flath et al. 2012b). Traut et al. (2012) propose an optimization model to minimize annual life-cycle costs for an EV fleet. Energy and emission costs are considered, as well as several engine and motor types, battery size, battery swing windows, the allocation of vehicles, and the allocation of home and workplace charging stations. Callaway and Hiskens (2011) explore conceptual requirements to develop and evaluate load schemes. Gottwalt et al. (2011) investigate the impact of smart appliances and variable prices under several tariffs regarding electricity bills of customers, and compare savings to required equipment. Lopes et al. (2009) and Dietz et al. (2011) assess several charging strategies for EVs in order to match energy generation and demand. Flath et al. (2012c) integrate a cluster analysis approach into the business intelligence environment to achieve a customer segment-specific energy tariff design.

However, combining a smart meter with a communication gateway, metering infrastructure and a management system (advanced metering) opens up new possibilities and gives EV drivers the chance to participate in demand response programs (Kranz 2011). Advanced metering research is based on the idea that EV drivers and energy suppliers exchange more than price information, and bridge “the communication gap between consumers and other energy systems’ parties by means of information and communication technologies” (Kranz 2011). Yang et al. (2009) find that advanced metering enables more efficient and anticipatory coordination between power generation and demand. Kranz (2011) analyzes customer acceptance of advanced metering devices. The economic impact of advanced metering is discussed in an overview by Faruqui et al. (2010). Bitar and Low (2012) suggest a market model for deadline-differentiated pricing of deferrable electric power services. Under this model costumers get financial incentives for giving the energy supplier a time frame with a deadline for deferrable power services. An example for such power services could be the charging process of EVs since they are often longer plugged in as they need for a full charge. In this example the time frames starts when the EV is plugged in and the deadline is the starting time of the next trip. Bitar and Low (2012) name the earliest-deadline-first strategy as an optimal scheduling policy for the supplier. This strategy provides customers with electric energy first, that communicated the earliest deadline. Furthermore Bitar and Xu (2013) show that the earliest-deadline-first allocation is not only an optimal scheduling policy for the energy supplier but can also be incentive compatible. That means all customers will truthfully provide the information of their specific deadlines. However, the authors do not quantify the benefit of such an allocation policy. Goebel (2013) proposes a comprehensive simulation-based business case analysis and shows that controlling charging behavior with the help of advanced metering may lead to significant cost savings. Schmidt and Busse (2013) use simplistic driving profiles and assume a fixed daytime for the latest end of charging to evaluate whether investments in smart EV charging technologies are a suitable alternative to an expansion of power plant capacities. Wagner et al. (2013) conduct a comprehensive simulation and use data from the internal parking guidance systems of two major German cities to compute a business case for a cluster of parking garages as operating instances for grid regulation. Brandt et al. (2013) investigate the economic benefit of an IS artifact, which coordinates the charging process of an EV dependent on historical data of the energy generation of a residential roof-top photovoltaic panel, the domestic demand and the driving behavior. Thereby the authors show the capability of ICT in adjusting the energy demand to the volatile energy supply on a local stage.

Nevertheless, none of these approaches perform an aggregate economic potential analysis of smart EV charging within a nationwide grid. Böning et al. (2010) find that the use of information exchange infrastructure “is more a result of regulation than of industry initiatives” (Römer et al. 2012; Böning et al. 2010). Thus, it appears necessary to analyze the business potential of ICT-supported communication with advanced metering devices and incentives to facilitate widespread market penetration.

The challenge of renewable energy integration

Renewable energy sources generate energy from resources that are continually replenished, e.g., sunlight or wind. The occurrence of these natural resources is not stable but volatile, leading to fluctuating energy generation. Since the behavior of households, industries and other energy demanders is uncertain, uncertain energy generation from renewable sources, as well as uncertain quantities of energy demand cause imbalances in the grid. One possible measure to capture imbalances of energy generation and demand is the residual load, which is the difference between energy demand, and the amount of energy generated from renewable energy sources at any given time. It thus constitutes the non-influenceable energy fluctuation, given that the demand is unmanaged and renewables are not disconnected from the grid, two conditions which should be avoided for economic reasons.

The residual load must be supplied with energy from conventional power plants and balanced through ESFs, power plants with a relatively short start-up phase, and energy imports (dena 2012). ESFs are more favorable to compensate short-term fluctuation, since the fuel consumption can be reduced by storing energy from renewables instead of switching conventional power plants on and off. Therefore the CO2-emission and the costs for energy production can be decreased by using ESFs (Moser et al. 2014). Furthermore conventional power plants provide only a relatively constant load, and ESFs have an efficiency factor of 80%, at most (Economist 2012). Energy imports and exports may not only lead to high payouts for the energy supplier, but also do not solve the problem of energy storage. By proceeding further with the energy turnaround, the share of renewables of the whole energy supply will increase significantly. Residual load volatility and grid imbalances are also expected to increase drastically (see Figure 1 (dena 2012)).

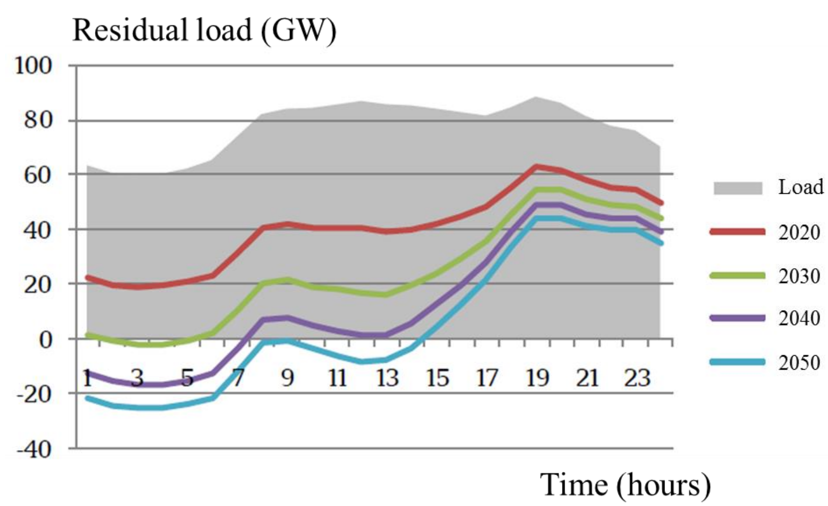

Figure 1. Residual loads forecast for an average German weekday in 2020 (dena 2012)

Consequently, it will become increasingly important for energy suppliers to decrease energy imbalances. In the following section, we will demonstrate how ICT can be used for demand-side management of EVs by means of manageable energy consumers, which are quickly available. They can be assigned to store energy surplus and decrease residual load volatility and, eventually, payouts for energy supplier and customers.

Model

In this section, we develop a generic formal model and evaluate its applicability in a multi-agent simulation. We consider daytime-specific driving behavior as well as season-specific traffic volume and use forecast data for residual loads in the year of 2020 to compare a smart charging strategy to immediate charging. In principle, the problem at hand could be solved with a dynamic programming model. However, a simulation is the more sensible approach, as the model considers many different persons involved, each with random parameters that are described by a variety of different distribution functions. These qualities make an analytical solution merely impossible.

We consider a setting with one energy supplier E and n EV drivers i, where $i = 1, \dots, n$. Generally, a more complex analysis under consideration of more advanced market conditions, such as trading opportunities or dynamic pricing mechanisms, could be performed without jeopardizing the validity of the results of this article.

We consider a certain timeframe which can be divided into T time periods, $t = 0, \dots, T$. In each period, the energy provider faces a certain residual load R_t measured in kW. We assume that the average residual load $\overline{R}$ can be delivered by conventional power plants, and is therefore irrelevant to our model. The deviation from the average $S_t = \overline{R} - R_t$ thus describes the over (+) or undercapacity (-) of the grid that must be balanced through charging/discharging of ESFs, e.g., pumped storage plants. Charging and discharging ESFs has efficiency factors of $0 < \eta_l < 1$ and $0 < \eta_u < 1$, respectively. Charging the ESF with an overcapacity of S_t therefore actually only charges $S_t \cdot \eta_l$, and causes losses of $S_t \cdot (1 - \eta_l)$, whereas discharging an undercapacity of S_t from the ESF requires S_t / η_u to be actually withdrawn from the ESF, and causes losses of $S_t \cdot \left(1 - \frac{1}{\eta_u}\right)$. The total energy lost due to the inefficiency of charging and discharging the ESF is therefore

$$\mathrm{L}_\eta = \sum_{\substack{t=0 \\ S_t > 0}}^{T} S_t \cdot (1 - \eta_l) + \sum_{\substack{t=0 \\ S_t < 0}}^{T} S_t \cdot \left(1 - \frac{1}{\eta_u}\right).$$

We assume opportunity cost for these energy losses of $c_c \cdot \mathrm{L}_\eta$, with c_c describing the cost of conventional energy per kWh. Moreover, running ESFs causes cost. To account for this cost, we assume that discharging 1 kWh of energy from an ESF causes cost c_S (dena (2008) aggregates the cost involved with ESFs into one value). If energy imbalance is over a certain threshold, it is possible that the payouts necessary to store additional energy are higher, e.g., another pumped storage plant must be activated, or a power plant must be shut down. For simplification, we omit this effect - which would strengthen the results of this paper even further - and assume c_S to be constant. The total cost C for the energy supplier due to surplus of energy generation or demand during T, then, are:

$$C = c_c \cdot \mathrm{L}_\eta + \sum_{\substack{t=0 \\ S_t < 0}}^{T} S_t \cdot c_S = c_c \cdot \left(\sum_{\substack{t=0 \\ S_t > 0}}^{T} S_t \cdot (1 - \eta_l) + \sum_{\substack{t=0 \\ S_t < 0}}^{T} S_t \cdot \left(1 - \frac{1}{\eta_u}\right) \right) + \sum_{\substack{t=0 \\ S_t < 0}}^{T} S_t \cdot c_S$$

The energy supplier aims at lowering C in order to increase its economic profit. This can be reached by lowering $|S_t|$.

Because each of E's n customers accounts for one EV, we will treat customers and EVs synonymously. Each EV features a certain charging level at every point of time $E_{i,t}$, and a maximum charging level, E_{max}, measured in kWh, (we assume E_{max} to be equal for all vehicles). EVs alternate between parking and driving during T. The individual durations of driving are modeled as exponentially distributed random variables $\tilde{d}_{d,i,\underline{t}}$ limited to the maximal range with regard to an EV's initial charging level. The individual (residual) durations for parking are denoted as $d_{p,i,\underline{t}}$ ($\underline{t}$ is the period in which parking began). Therefore, we find that $d_{d,i,\underline{t}} = min(\tilde{d}_{d,i,\underline{t}}, E_{i,t}/u)$, with u denoting the EV's energy usage per period, (assumed to be constant and equal for all EVs). At the end of driving in t, the charging level of an EV will thus be $E_{i,t} = E_{i,t'} - d_{d,i,\underline{t}'} \cdot u$, with $t' = \underline{t}'$ denoting the starting period of the previous trip.

During parking times, an EV may be connected to a battery-charging infrastructure. The current charging infrastructure is not developed nationwide, e.g., the necessary grid connection can nowadays only be provided during half of the day in Germany (Wagner et al. 2013). In accordance with the work of Kempton and Tomić (2005a), we assume that EVs can be charged in 75% of all cases by 2020. Transport losses between different localities of energy generation and EV charging are disregarded. Each EV i arrives at a charging device with a specific state of charge $E_{i,t}$. We assume the primary concern of all EV drivers is to have a fully-charged EV when starting a trip, or - if parking time is not sufficient to charge the battery completely - the maximum charging level possible. We furthermore assume EV drivers to be indifferent towards the charging status until they start the next trip. The secondary concern of all EV drivers is to minimize the cost for charging the EV. Consequently, if there is either not enough or just the parking time available to fully charge the EV, (i.e., if $d_{p,i,\underline{t}} \leq (E_{max} - E_{i,t})/v$ with v denoting the amount of energy being charged in 1 period), the EV will be charged immediately upon being plugged in. Otherwise, the EV may be charged at any time as long as it is fully charged in period $t + d_{p,i,\underline{t}}$. We do not consider load-dependent charging speed, but instead assume linear charging progress (Qian et al. 2011).

As many EV drivers might prefer to maintain a certain flexibility at any time, it might be necessary to define a minimal amount of energy that is charged right away in any given situation, (e.g., to go to a hospital or to the nearest supermarket). Thus, we regard an emergency driving time $d_{d,em}$ that an EV should always be able to reach. If the remaining charging level of a parking EV is not sufficient for the emergency driving time, it will be charged independently from the residual load until the necessary charging level for $d_{d,em}$ has been achieved, (i.e. charge an EV as long as $E_{i,t}/u < d_{d,em}$).

Information exchange and its implications

Without advanced metering, the energy supplier has no information about the parking duration $d_{p,i,\underline{t}}$, and is thus forced to charge each parked car immediately. Only this strategy fulfils the EV drivers' main objective, which is to start again with a full battery or with the maximum possible charging level. In the following section, we will refer to this charging strategy as "immediate charging." We assume that with ICT-based information exchange, the energy supplier will not only know the current charging level $E_{i,t}$, but also the parking time $d_{p,i,\underline{t}}$ truthfully provided by the EV drivers. It is possible that the actual parking time differs from the parking time submitted to the energy supplier. In an effort to simplify, we neglect anything other than planned trips, though other situations might be a valuable subject for future research. With this information, the energy supplier is able to compare the necessary charging time $(E_{max} - E_{i,t})/v$ with the parking time available in order to schedule an individual charging strategy for each EV. While more information might allow for more sophisticated scheduling strategies, we describe a very simple smart strategy using this information, as well as its merits, in the following section.

The difference $b_{i,t} = d_{p,i,\underline{t}} - (E_{max} - E_{i,t})/v$ can be interpreted as the buffer a parked EV i has for being charged in period t. As long as $b_{i,t} > 0$, it is not necessary to charge the EV. As time goes by without charging, $(E_{max} - E_{i,t})/v$ will stay constant while $d_{p,i,\underline{t}}$ will diminish. Since Bitar and Low (2012) already presented earliest-deadline-first as an optimal scheduling policy for the energy supplier, we want to apply this policy within the following greedy algorithm:

1. Identify all EVs that are ready for charging, i.e., they are parking with $(E_{max} - E_{i,t}) > 0$.
2. Charge all EVs with $E_{i,t}/u < d_{d,em}$.
3. Charge all EVs with $b_{i,t} \leq 0$.
4. As long as $S_t > 0$, charge the vehicles with the lowest buffers $b_{i,t}$ first (the charged energy is then subtracted from S_t).

This smart-charging algorithm ensures that as few EVs as possible are charged when $S_t \leq 0$, and that as many EVs as possible are charged when $S_t > 0$. Compared to the immediate-charging algorithm, the smart-charging algorithm minimizes the average $|S_t|$, and thus reduces the charging/discharging of ESFs. Furthermore, it preserves the highest possible flexibility in terms of the total buffer available, as EVs with a low buffer are charged first and EVs with a high buffer stay on the list for later charging. Although a greedy algorithm is only a heuristic approach, it delivers an optimal solution under the given assumptions. It should be mentioned that this would not be the case for an increasing c_S with an increasing S_t, as it might be sensible to postpone charging in order to avoid even higher peaks of S_t. However, since this element would make the model much more complex and would only increase the possible economic benefits of smart charging, we refrain, for now, from integrating this into our model.

To evaluate the economic benefit of the information needed to implement the algorithm, we must compare the payouts of the immediate-charging strategy with those of the smart-charging strategy. Hevner et al. (2004) name simulation as a legitimate means to evaluate design-oriented research. Therefore, we built a multi-agent simulation which is based upon real-world data to demonstrate that using advanced metering technology to transfer trip information will yield better results in practice than immediate charging will. The simulation was built in Java using the MASON library, which is a multi-agent simulation library. Among other things this library contains a sophisticated random number generator for various density functions.

Data

For our simulation, we use forecast data for residual loads of an average weekday in winter, as well as an average summer Saturday in Germany in the year of 2020 with positive and negative residual loads (dena 2012). In accordance with the German plans for EV integration (Bundesregierung 2009), we assume 1 million EVs on German streets by 2020, but performed also a simulation run with 200,000, and one with 5 million EVs to analyse validity and sensitivity of our results. We use season-specific traffic volumes according to BMVBS (2010) to model different driving behaviour for winter and summer. In order to take different driving profiles over day into account and to picture daytime-specific EV usage, we use real world data of BMVBS (2010). Thus, each EV is assigned a trip starting probability during each time of the day, again for both a winter weekday and a summer Saturday. We consider all EVs to be of the same kind, and calculate with a battery capacity of $E_{max}=22$ kWh and an average of $u=0.154$ kWh/min energy consumption for each EV based on the data of de la Fuente Layos (2007). The batteries of all EVs can be charged by charging devices at equal charging speed, for which we use $v=0.0969$ kWh/min based on Qian et al. (2011). We calculate with an average driving time of $\tilde{d}_{d,i,\underline{t}} =13$ minutes (derived from de la Fuente Layos 2007) which is varied exponentially. We use $\eta_l =0.86$ as the ESF charging efficiency factor, and $\eta_u =0.88$ as the ESF discharging efficiency factor (dena 2008). Furthermore, we calculate with $c_S =0.1065$ € for ESF costs, and $c_c =0.116$ € for opportunity costs for energy losses per kWh (dena 2008). For the emergency driving time we also use two values to investigate the effect of this variable. For that, we run the simulation for an emergency driving time of 10 minutes and for an emergency driving time of 20 minutes. As mentioned before, we take into account that charging infrastructure, is available only in 75% of all cases where a driver parks an EV to start a charging process. The probability of charging infrastructure availability as well as the trip starting time of the EVs and the exponential distributed driving time constitute the stochastic component of the simulation. Table 1 gives an overview of all input values and literature sources.

Table 1. Data input for the simulation

Variable	Description	Value	Distribution	Source
n	Number of EVs	1,000,000 (200,000; 5,000,000)	-	Bundesregierung (2009)
T	Runtime	2 days (1 winter, 1 summer)	-	-
R_t	Residual load for a weekday in winter	-	Acc. to dena (2012)	dena (2012)
	Residual load for a day of a summer weekend	-	Acc. to dena (2012)	dena (2012)
-	Trip starting times for a weekday in winter	-	Acc. to BMVBS (2010)	BMVBS (2010)
	Trip starting times for a day of a summer weekend	-	Acc. to BMVBS (2010)	BMVBS (2010)
$\tilde{d}_{d,i,\underline{t}}$	Driving time	13 min	exponential	Derived from de la Fuente Layos (2007)
$d_{d,em}$	Emergency driving time	10 min (20 min)	-	-
-	Traffic volume summer	-	-	BMVBS (2010)
	Traffic volume winter	-	-	BMVBS (2010)
v	EV charging speed	0.0969 kWh/min	-	Derived from Qian et al. (2011)
E_{max}	EV battery capacity	22 kWh	-	-
u	Energy consumption per min	0.154 kWh/min	-	de la Fuente Layos (2007)
η_l	ESF charging efficiency	0.86	-	dena (2008)
η_u	ESF discharging efficiency	0.88	-	dena (2008)
c_S	Costs for discharging 1 kWh from ESF	0.1065 €/kWh	-	dena (2008)
c_c	Opportunity costs for energy losses per kWh	0.116 €/kWh	-	dena (2008)
-	Probability of charging infrastructure availability	75%	-	Derived from Kempton and Tomić (2005a)

Simulation results

Before the actual simulation starts, there are the model iterations for two days conducted to get realistic initial charging levels for all EVs. In the following we will illustrate the results of the simulation with 1 million EVs and an emergency driving time of 10 minutes. As we want to get representative results, we run the simulation twice, first with the residual loads and the trip starting times of an average Saturday in summer and second for the specific parameter values of an average Tuesday in winter. The values of the remaining parameters can be seen in table 1.

With the immediate charging strategy, the EVs are charged as long as they are plugged in and not fully charged. This has the consequence, that EV charging is conducted independently from grid over- or undercapacities. Grid undercapacity in particular is neither compensated nor counteracted by reduced EV charging. Figure 2 shows the numbers of EV charging and the grid imbalances over the period of one average Saturday in summer and an average Tuesday in winter of 2020.

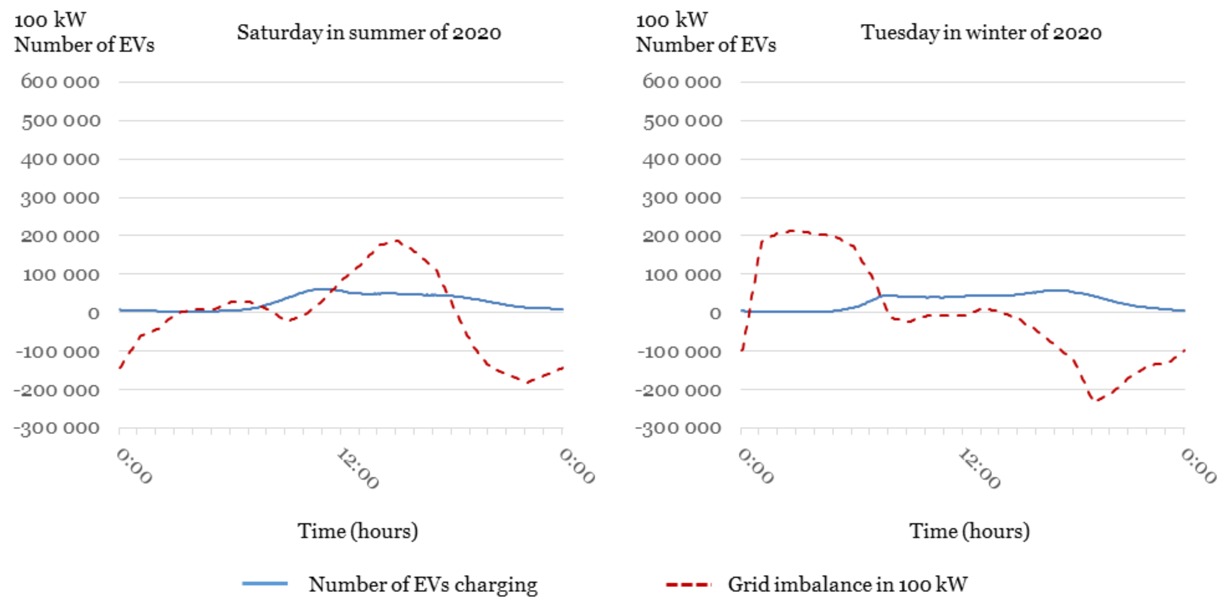

Figure 2. Immediate charge

As illustrated in Figure 3, an information exchange-based smart charging strategy produces an unsteady charging profile, with high demand where overcapacity is available and low demand in times of undercapacity. In periods of undercapacity, only the plugged in EVs are being charged that feature no or a negative buffer or that need emergency charging. In periods of overcapacity, all plugged in EVs are being charged that feature a charging level below maximum. As can be seen from Figure 3, this demand shift is even able to completely balance the grid between 12:25pm and 01:10pm during an average winter Tuesday and between 03:15am and 04:00am during an average day of a summer weekend in 2020.

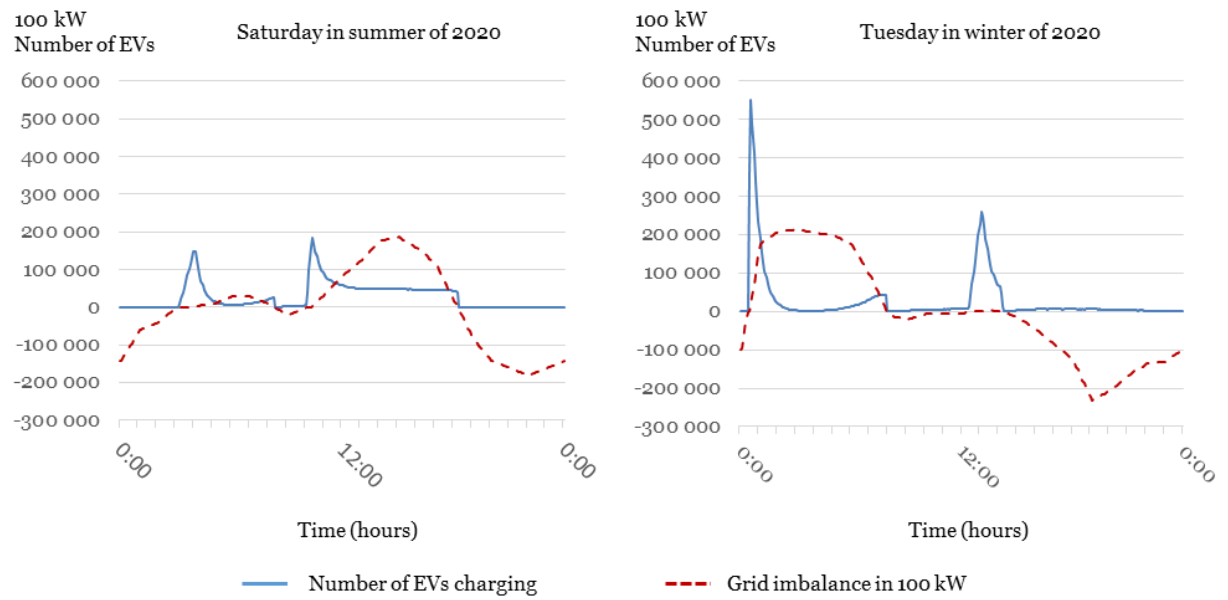

Figure 3. Information exchange based smart charging

Figure 4 presents the volatility reduction as the absolute difference between the grid imbalances when applying the smart and the immediate charging strategy.

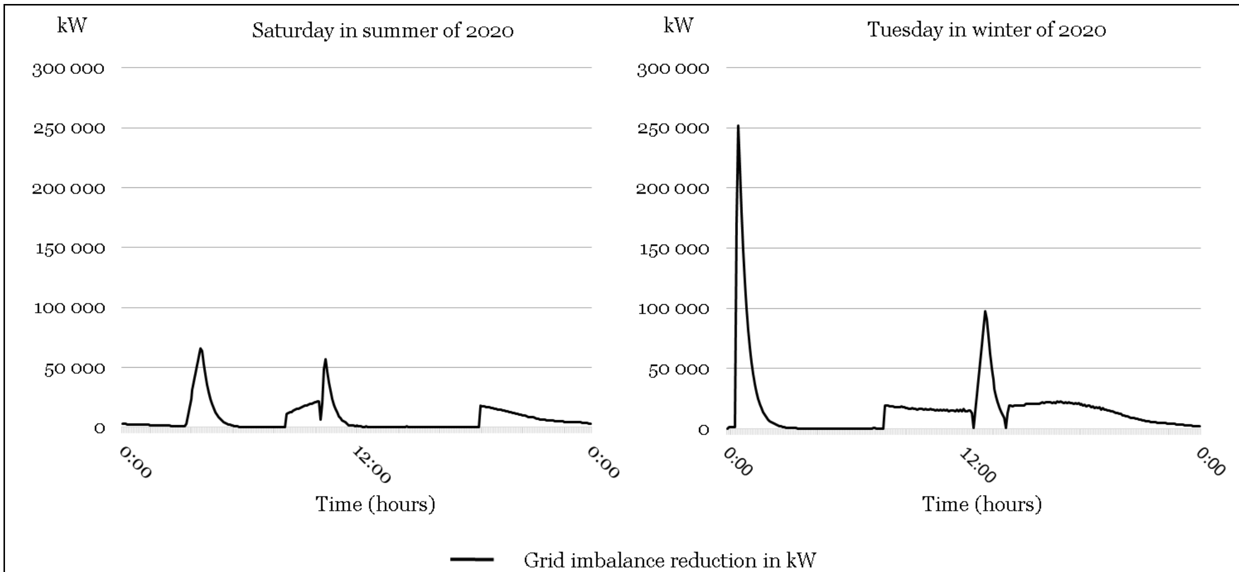

Figure 4. Grid imbalance reduction

To compare the monetary effects of immediate and smart charging, we need to compare the necessary balancing costs through ESFs for both scenarios. The total balancing costs are compounded of the variable costs of ESFs and the costs due to ESF efficiency losses. We compare EVs' state of charging at the beginning and at the end of the considered periods, and remove the possible bias (EV charging loss) from the economic potential calculation. Charging loss is calculated as the monetarized difference between the initial charging level (at midnight) and the charging level at the end of the simulation for all EVs. Table 2 describes the outcomes for the two charging strategies.

Table 2: Comparison of immediate and smart charging (in million €)					
	Strategy	**ESF cost**	**ESF efficiency loss**	**EV charging loss**	**Total cost C**
winter	immediate	13.605	5.098	0.000	18.702
	smart	13.336	5.001	0.001	18.338
summer	immediate	10.571	3.976	0.000	14.548
	smart	10.456	3.935	0.001	14.392

With respect to the model assumptions, our simulation results in a significant amount of savings - approximately 364,000 € for the considered day in winter, and 156,000 € for the day in summer. As can been seen from Table 2, the charging loss is negligible. These outcomes are calculated as the mean of the results of 50 simulation runs. In table 3 there are several statistical measures summarized.

Table 3: Statistical measures of the total cost C for 50 simulation runs (in million €)						
	Strategy	**Minimum**	**Median**	**Maximum**	**Mean**	**Standard deviation**
winter	immediate	18.6998	18.7014	18.7034	18.7016	0.0008198
	smart	18.3355	18.3384	18.3409	18.3382	0.0011795
summer	immediate	14.5458	14.5475	14.5487	14.5475	0.0006001
	smart	14.3910	14.3917	14.3927	14.3918	0.0004164

The standard deviation of the results is very small. With that small standard deviation and the fact that a complete simulation run including both charging strategies for a day in winter as well as for a day in summer needs about one hour, we only conducted 50 simulation runs with the described input factors.

With a higher emergency driving time, the savings get a bit smaller. For an emergency driving time of 20 minutes the simulation calculates savings at a height of approximately 358,000 € for an average weekday in winter and 154,000 € for the day in summer. This is because a higher emergency driving time lowers the 'flexible' battery capacity. Since having 1,000,000 EVs on German streets by 2020 is currently a political objective, while other scenarios can become also reality, we conducted a short sensitivity analysis with 200,000 cars and 5 million cars, through which we found savings of approximately 71,000 € in winter (31,000 € in summer) and 1,728,000 € in winter (833,000 € in summer), respectively.

Primarily the energy provider earns the benefits from the smart charging strategy in terms of the reduction of the ESF usage and as a result a decrease of costs. The actual amount to be saved depends, however, on the drivers and their willingness to provide the necessary trip information to the energy supplier. It is thus necessary to develop a well-designed incentive system with regard to the revealed economic potential. Therefore the energy provider could use these savings to incentivize the drivers to disclose this information (Bitar and Low 2012). For 1 million cars, achievable savings are an average of 0.364 € per car (0.156€ in summer), or 7.3% (3.1% in summer) of the approximately 5 € average cost for a *complete* battery charge of an EV with today's prices. Keeping in mind that not all cars are completely charged in one day, and that some drivers will earn higher rebates due to longer parking times while others will earn lower or no rebates due to frequent usage of the car, this amount should be a good basis for incentivizing drivers. For 200,000 cars and 5 million cars, the amount should be equally sufficient for EV drivers to reveal their driving schedule.

Besides the economic potential, a smart charging strategy bears also an ecological benefit. ESFs do not only need much space and resources to be built. Moreover the usage of ESFs is associated with efficiency losses. By applying the smart charging strategy the energy demand is shifted and so the amount of energy being stored declines. In our simulation the reduction of the usage of ESFs by the smart charging strategy decreases the efficiency losses by approximately 179 kWh for the day in summer and 460 kWh for the day in winter within a scenario with 1 million EVs. These results were also approved by scenarios with 200,000 EVs and 5 million EVs.

However, the costs of implementing smart charging processes have to be born - advanced meters, as well as smart charging stations, would have to be installed at homes, workplaces, and also in public zones. Thus, we will discuss a possible scheme that might offer the necessary information exchange incentives to EV drivers in the following section.

A pricing scheme for smart EV charging

As mentioned before, EV drivers considered in our model follow two objectives: (1) to reduce their energy cost and (2) to have their car fully charged for the next trip. We assume that financial incentivisation of information exchange is conducted by energy price deduction.

Due to flexibility, each EV driver will prefer the car to be charged as quickly as possible. However, EV drivers will not be willing to pay for an earlier charge if they do not plan to use the EV. Consequently, EV drivers cannot be incentivized by an energy price deduction to disclose their parking time unless this price deduction depends on the actual duration of parking $d_{p,i,\underline{t}}$. For example, EV drivers might exploit a constant energy price deduction by submitting information about a much earlier starting time of the next trip than what is actually planned. Thus, lower energy prices for longer parking times will incentivize EV drivers to disclose the actual starting time of their next trip. Therefore, a meaningful price function decreases in response to the parking time $d_{p,i,\underline{t}}$, and thus rewards longer parking times with a lower energy price.

From the energy supplier's perspective, we can furthermore deduct the following requirement for a pricing function: The price's upper bound $\hat{p}$ corresponds to the driver's regular energy tariff. If the EV is required to be charged immediately ($b_{i,t} \leq 0$), i.e., no demand-shifting benefits can be realized, there is no reason to treat it differently from other power-consuming devices.

All in all, a meaningful price function p depends on the parking duration $d_{p,i,\underline{t}}$, is constant at $\hat{p}$ until $(E_{max} - E_{i,t})/v$, and is then monotonically decreasing. Exemplary function curves, which depict possible price functions, are illustrated in Figure 5.

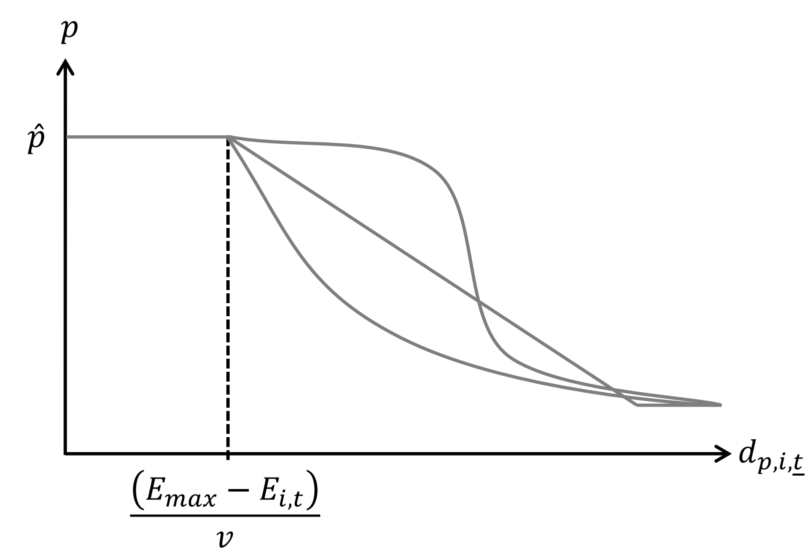

Figure 5: Possible price functions for information exchange-based EV charging

Determining a tangible pricing function requires a closer examination of the connection between energy price and the EV drivers' willingness to provide truthful trip information to the energy supplier (Bitar and

Xu 2013). The findings presented in this paper thus provide a basis for future behavioural research focussing on this connection.

Summary, limitations and outlook

In this article, we evaluated the aggregate economic benefit of an advanced metering approach where EV drivers provide information about the start of the next trip to the energy supplier. After an overview of related literature, we introduced a main challenge of renewable energy integration and developed a formal model to demonstrate how energy suppliers can benefit from trip information. We presented the data, which we used to conduct a simulation approach for the German energy grid and discussed a pricing scheme leveraging the ICT-supported saving potential. Nevertheless, several assumptions in our work need to be examined critically, and may build the basis for future research.

We did not take the perspective of an energy supplier, but rather treat the supply side of the energy grid as a whole. Individual suppliers may use more instruments to counteract energy imbalances, like forecast models or energy trading opportunities with futures and options. Moreover, we simplify the model in various ways, e.g., by assuming that parking is not aborted before the scheduled ending and assuming uniform vehicle and charging infrastructure properties (e.g., linear charging progress, equal battery capacity and equal charging speed). Also, we do not consider adoption obstacles such as privacy concerns of users, i.e., skeptics might be prejudiced towards big (energy) companies knowing their driving behavior and whereabouts. Finally, we do not analyze the exact coherence between energy pricing and the customers' willingness to disclose trip information and provide demand-side flexibility to the energy supplier. Enhancing our model by considering exact pricing functions seems promising, e.g., for behavioral research approaches. However, our article illustrated that advanced metering combined with incentive-compatible pricing structure bears enormous economical and also ecological potential. Thus, we think that our work may contribute to leveraging the potential of ICT-based information exchange in the context of market penetration of EVs to counteract the challenges of the energy turnaround with regard to energy imbalances in the grid.

Acknowledgements

This research was (in part) carried out in the context of the Project Group Business and Information Systems Engineering of the Fraunhofer Institute for Applied Information Technology FIT.

References

Albadi, M. H., and El-Saadany, E. 2008. "A summary of demand response in electricity markets," *Electric Power Systems Research* (78:11), pp. 1989-1996.

BMVBS (Bundesministerium für Verkehr, Bau und Stadtentwicklung) 2010. "Mobilität in Deutschland 2008".

Böning, S., Dämbkes, A., and Reichhart, P. 2010. "Die M2M-Industry-Map Deutschland," *E-Plus*.

Bitar, E., and Low, S. 2012. "Deadline Differentiated Pricing of Deferrable Electric Power Service,"*51st IEEE Conference on Decision and Control,* pp. 4991-4997.

Bitar, E., and Xu, Y. 2013. "On incentive compatibility of deadline differentiated pricing for deferrable demand," *52nd IEEE Conference on Decision and Control,* pp. 5620-5627.

Brandt, T., Feuerriegel, S., and Neumann, D. 2013. "Shaping a Sustainable Society: How Information Systems Utilize Hidden Synergies between Green Technologies," *Thirty Fourth International Conference on Information Systems, Milan*.

Bundesregierung Deutschland 2009. "Nationaler Entwicklungsplan Elektromobilität der Bundesregierung," *Berlin*. Retrieved from http://www.bmu.de/files/pdfs/allgemein/application/pdf/nep_09_bmu_bf.pdf.

Callaway, D., and Hiskens, I. A. 2011. "Achieving controllability of electric loads," *Proceedings of the IEEE* (99:1), pp. 184-199.

Christian, R. 2010. "Smart grids are the key enabler for green energy system deployment around the globe," *1st IEEE Smart Grid World Forum*.

Clement, K., Haesen, E., and Driesen, J. 2009. "Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids," *Power Systems Conference and Exposition*, pp. 1-7.

Copeland, T. E., Weston, J.F., and Shastri, K. 2005. "Financial Theory and Corporate Policy," *Boston, MA: Pearson Education Inc*.

De La Fuente Layos, L. A. 2007. "Mobilität im Personenverkehr in Europa," *Statistik kurz gefasst*. Retrieved from http://www.eds-destatis.de/de/downloads/sif/sf_07_087.pdf.

dena (Deutsche Energie-Agentur) 2012. "Integration der erneuerbaren Energien in den deutschen/europäischen Strommarkt," Retrieved from http://www.dena.de/fileadmin/user_upload/Presse/Meldungen/2012/Endbericht_Integration_EE.pdf.

dena (Deutsche Energie-Agentur) 2008. "Elektrizitätswirtschaftliche und energiepolitische Auswirkungen der Erhebung von Netznutzungsentgelten für den Speicherstrombezug von Pumpspeicherwerken," Retrieved from http://www.dena.de/fileadmin/user_upload/Publikationen/Energiedienstleistungen/Dokumente/Pumpspeicherstudie.pdf.

Dietz, B., Ahlert, K., Schuller, A., and Weinhardt, C. 2011. "Economic benchmark of charging strategies for battery electric vehicles," *PowerTech IEEE Trondheim*, pp. 1-8.

Economist 2011. "Nuclear? Nein, danke: A nuclear phase-out leaves German energy policy in a muddle," Retrieved from http://www.economist.com/node/18774834.

Economist 2012. "Packing some power," Retrieved from http://www.economist.com/node/21548495?frsc=dg|a.

Faruqui, A., Harris, D., and Hledik, R. 2010. "Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment," *Energy Policy* (38:10), pp. 6222-6231.

Flath, C., Ilg, J., and Weinhardt, C. 2012. "Decision Support for Electric Vehicle Charging," *18th Americas Conference on Information Systems (AMCIS)*, paper 14.

Flath, C., Gottwalt, S., and Ilg, J. P. 2012. "A Revenue Management Approach for Efficient Electric Vehicle Charging Coordination," *45th Hawaii International Conference on System Science (HICSS)*, pp. 1888-1896.

Flath, C., Nicolay, D., Conte, T., van Dinther, C., and Filipova-Neumann, L. 2012. "Cluster Analysis of Smart Metering Data: An Implementation in Practice," *Business & Information Systems Engineering* (4:1), pp. 31-39.

General Motors 2011. "Chevrolet Volt Technology," Retrieved from http://www.chevroletvoltage.com/images/stories/VoltAge_U_Content/about%20volt%20powerpoint.pdf.

Goebel, C. 2012. "On the business value of ICT-controlled plug-in electric vehicle charging in California," *Energy Policy* (53:1), pp. 1-10.
Gottwalt S., Ketter W., Block C., Collins J., and Weinhardt, C. 2011. "Demand side management - A simulation of household behavior under variable prices," *Energy Policy* (39:12), pp. 8163-8174.
Hevner, A. R., March S. T., Park J., and Ram, S. 2004. "Design science in information systems research," *Management Information Systems Quarterly* (28:1), pp. 75-106.
Heydt, G. T. 1983. "The impact of electric vehicle deployment on load management straregies," *IEEE Transactions on Power Apparatus and Systems* (5), pp. 1253-1259.
Kempton, W., and Tomić, J. 2005a. "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources* (144:1), pp. 268-279.
Kempton, W., and Tomić, J. 2005b. "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources* (144:1), pp. 280-294.
Kley, F., Lerch, C., and Dallinger, D. 2011. "New business models for electric cars - A holistic approach," *Energy Policy* (39:6), pp. 3392-3403.
Kranz, J. 2011. "Studies on Technology Adoption and Regulation of Smart Grids," *Berlin: epubli GmbH*.
Lopes, J. P., Polenz, S. A., Moreira, C. A., and Cherkaoui, R. 2010. "Identification of control and management strategies for LV unbalanced microgrids with plugged-in electric vehicles," *Electric Power Systems Research* (80:8), pp. 898-906.
Lopes, J. P., Soares F. J., and Almeida, P. R. 2009. "Identifying management procedures to deal with connection of electric vehicles in the grid," *Proceedings from the IEEE Bucharest Power Tech Conference*, pp. 1-8.
Mattern, F., Staake, T., and Weiss, M. 2010. "ICT for Green: How Computers Can Help Us to Conserve Energy," Retrieved from http://www.im.ethz.ch/publications/ICTforGreen.pdf.
Moser, A., Rotering, N., and Schäfer, A. 2014. "Unterstützung der Energiewende in Deutschland durch einen Pumpspeicherausbau," Retrieved from http://www.wasserkraft.info/application/media/documents/Abschlussbericht_RWTH_PSW_Voith_final.pdf.
Qian, K., Zhou, C., Allan, M., and Yuan, Y. 2011. "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Transactions on Power Systems* (26:2), pp. 802-810.
Römer, B., Reichhart, P., Kranz, J., and Picot, A. 2012. "The role of smart metering and decentralized electricity storage for smart grids: The importance of positive externalities," *Energy Policy* (50), pp. 486-495.
Schmidt, J., and Busse, S. 2013. "The Value of IS to Ensure the Security of Energy Supply – The Case of Electric Vehicle Charging," *Proceedings of the Nineteenth Americas Conference on Information Systems, Chicago*.
Schuller, A., Ilg, J., and van Dinther, C. 2012. "Benchmarking electric vehicle charging control strategies," *IEEE PES*, pp. 1-8.
Soares, F., Lopes, J. P., Almeida, P. R., Moreira, C., and Seca, L. 2011. "A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid," *PSCC*, pp. 22-26.
Strbac, G. 2008. "Demand side management: Benefits and challenges," *Energy Policy* (36:12), pp. 4419-4426.
Subramanian, A., Garcia, M., Dominguez-Garcia, A., Callaway, D., Poolla, K., and Varaiya, P. 2012. "Real-time Scheduling of Deferrable Electric Loads," *American Control Conference*.
Sundström, O., and Binding C. 2010. "Optimization methods to plan the charging of electric vehicle fleets," *International Conference on Control, Communication and Power Engineering*, pp. 28-29.
Tate, E. D., Harpster, M. O., and Savagian, P. J. 2008. "The electrification of the automobile: From conventional hybrid, to plug-in hybrids, to extended-range electric vehicles," Retrieved from http://www.media.gm.com/content/dam/Media/microsites/product/volt/docs/paper.pdf.
Traut, E., Hendrickson, C., Klampfl, E., Liu, Y., and Michalek, J. 2012. "Optimal Design and Allocation of Electrified Vehicles and Dedicated Charging Infrastructure for Minimum Life Cycle Greenhouse Gas Emissions and Cost," *Energy Policy* (51), pp. 524-534.
Wagner, S., Brandt, T., and Neumann, D. 2013: "Beyond Mobility – An Energy Informatics Business Model For Vehicles In the Electric Age," *Proceedings of the Twenty First European Conference on Information Systems, Utrecht*.
Yang, Z., Lee, W., and Lam, H. 2009. "Collaboration Interface in Smart Metering Scheme," *The 15th International Conference on Electrical Engineering*, pp. 1-6.