Applying Demand Response Programs for Electric Vehicle Fleets

Completed Research Paper

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Abstract

In this study, we demonstrate the contribution of IS-supported demand response (DR) programs to the development of a sustainable transport sector. Based on the energy informatics framework, we develop an IS artifact that can be used to apply DR programs for electric vehicle (EV) fleets. Furthermore, we quantify one DR program in economic terms by analyzing data gathered in an electric mobility project with a car-sharing provider that uses EVs. The findings indicate that fleet operators can expect significant cost savings when applying DR programs; energy procurement costs can be reduced significantly by adjusting the time of energy use. Applying DR programs therefore has the potential to make EV fleets economically sensible because the already existing operational cost advantage can be further increased. Consequently, DR for EVs can foster sustainable development, as higher profitability could promote the market penetration of eco-friendly vehicles.

Keywords

Demand Response, Green IS, Energy Informatics, Electric Vehicles.

Introduction

Many governments currently aim to establish a future energy system that includes sustainable energy generation, reduced energy intensity of demand, and a more effective and sustainable use of energy (REN 21 2011; Harmelink et al. 2006). The main drivers for this development are the irreversible depletion of fossil fuels, the threat of climate change, and increasing environmental pollution caused by the use of fossil fuels (Elliot 2011; IPCC 2007). Therefore, some governments, such as Germany's, have determined various energy- and climate-related targets in order to shape a sustainable energy system. One of these goals is to reduce CO_2 emissions in the transport sector by at least 80% by 2050 compared to the 2008 level (BMWi and BMU 2010). This is deemed necessary because road transport is responsible for one-fifth of greenhouse gas emissions in the European Union (European Environment Agency 2012). Electric vehicles (EVs) are seen as an important factor in reducing road emissions. However, as their economic viability is constrained, the market penetration of EVs is still very low; several studies (e.g., Propfe et al. 2012; Thiel et al. 2010) have shown that the higher initial acquisition costs of EVs compared to conventional vehicles cannot be offset by the lower operating costs. One possibility for meeting this challenge is applying demand response (DR) programs for EVs. In general, DR refers to the consumer's ability to alter his or her energy consumption pattern in response to time-dependent electricity prices (Strbac 2008). Applying DR for EVs thus offers the opportunity to reduce energy procurement costs by shifting charging processes to off-peak hours (Lyon et al. 2012). In addition, DR programs create

energetic advantages because they can be used for balancing power supply and demand (Albadi and El-Saadany 2007).

Various studies identify energy-intensive industries as primary target groups for DR programs (e.g., Paulus and Borggrefe 2011; von Roon and Gobmaier 2010). Technical innovation in the field of information and communication technology (ICT) – such as advanced metering infrastructure (AMI) or smart meters with a communication gateway – also enable households and small commercial consumers to engage in DR programs (Kranz 2011). However, additional information systems (IS) are required for DR to compute the difference between expected and actual electricity wholesale prices and derive the optimal decision to shift demand at a given time (Feuerriegel et al. 2012). These kind of IS fall under the umbrella of Green IS as they form a base for DR and enable end users to take part in the smart grid (Melville et al. 2010).

IS are also required to enable fleet operators – for example, car-sharing operators using EVs – to participate in DR programs. To control a charging process (e.g., interruption during price peaks), however, it is necessary for the fleet operator to predict electricity demand and thus know the margin for load-shifting per charging process in advance (Geelen et al. 2013). In addition, electricity prices must be known beforehand. Surprisingly, most studies investigating the potential of DR programs for EV fleets ignore these facts. In line with these thoughts, our paper introduces a novel IS artifact that can be used to apply DR programs for EV fleets without restricting mobility needs. This leads us to the first research question:

> *RQ1:   How does an information system need to be designed to apply DR for EV fleets?*

By significantly decreasing energy procurement costs, the application of DR programs can make a valuable contribution to ensuring that these vehicles become economically competitive. Most related publications assessing the economic potential of controlled charging concepts, however, lack real-word data and therefore the results are missing external validity. To overcome this issue, we use data from a car-sharing operator in Germany to realistically assess the economic potential of applying a DR program for fleet operators and address the following second research question:

> *RQ2:   What are the economic potentials resulting from the application of a suitable DR program for an electric vehicle fleet?*

Our study thus addresses the issue of how IS-supported DR programs for EVs can save energy procurement costs for a company using EVs, thereby acting as a driving force for sustainable solutions in organizations. The remainder of this paper is organized as follows. Section 2 examines the fundamentals of DR in general and DR programs for EVs. Section 3 then presents an IS artifact that can be used to apply DR for EV fleets. In Section 4 we develop a prediction model required for the application of DR programs and then quantify one DR program in economic terms; the corresponding results are provided in Section 5. In Section 6, we discuss the findings and limitations of our research endeavor, which leads us to the conclusion presented in Section 7.

Background

The Role of Demand Response in Energy Informatics

Demand response can be defined as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" (U.S. DOE 2006). There has been a growing number of IS-related research publications on DR since Watson et al. (2010) emphasized the importance of IS research in increasing the efficiency of energy demand and supply systems. Subsumed under the terms 'Green IS' and 'Green IT,' research efforts have been made to reveal and apply the potential advantages of IS to sustainability dimensions, especially at the interface of IS and energy (Kossahl et al. 2012). For instance, Feuerriegel et al. (2012) and Bodenbenner et al. (2013) analyze how IS designs can contribute to the realization of demand response systems. In addition, Corbett (2011) reveals how IS may increase energy efficiency, while Watson et al. (2013) present a conceptual design for a DR system based on the trading of consumption rights. Strüker and van Dinther (2012) establish that IS play an important role in applying DR, as investments in smart grid technologies and ICT are required to interact with customers. For

example, communication systems are responsible for smooth and standardized real-time data exchange between all DR partners (e.g., utility, grid operator, and consumer). Furthermore, customers need information about electricity prices and the required usage alteration. To do so, an AMI including hardware, software, communication, and data management is used, enabling two-way communication between the utility's network and the customer's smart meters (Strüker et al. 2011).

Several benefits associated with DR can be identified. First, it supports the deployment of renewable energy by smoothing out power fluctuations (Azami and Fard 2008). Adapting electricity demand to volatile supply also leads to a reduction of price volatility in the electricity spot market. Furthermore, system reliability can be increased by reducing electricity demand at critical load times (Bradley et al. 2013; Strbac 2008). In general, DR programs can be divided into two categories that influence behavior on the consumer side: incentive-based programs and price-based programs. Incentive-based programs offer payments to participating customers (e.g., bill credits) to reduce their electricity consumption as required by the program sponsor; this may be triggered by grid reliability problems or price peaks. Price-based programs provide participating customers time-dependent rates reflecting the costs of generating and delivering electricity (Palensky and Dietrich 2011).

Demand Response of EVs

Several studies (e.g., Geelen et al. 2013; Wang et al. 2011) have identified EVs to be particularly suitable for participating in DR because, on average, they are used only during 4% of the day; the resulting idle times can be exploited by shifting the corresponding charging processes (Gu et al. 2013). Furthermore, charging a large number of EVs in an uncontrolled manner results in a significant load that would probably jeopardize power grid security (Schmidt and Busse 2013; Luo et al. 2011).

To date, most research has focused on two DR programs for EVs: the vehicle-to-grid (V2G) concept and smart charging. Within the V2G concept, EVs can provide utility services (incentive-based DR programs) by supplying power to the grid for stabilization and peak-time supply (Kempton and Tomić 2005). The feasibility of this DR program for EVs, however, is limited because regulatory requirements on most energy markets are too strict. For example, an actor on the ancillary market in Germany must offer a minimum of 5 MW of energy (regelleistung.net 2015). Moreover, technical requirements (e.g., regarding reaction time) are too high for smaller providers of flexible loads (Schmidt et al. 2014). Therefore, this DR program cannot be realized for EVs under the prevailing conditions.

The main goal of smart charging concepts is to shift energy consumption from peak to off-critical hours. To achieve this goal, electricity suppliers can give customers monetary incentives (e.g., real-time pricing) to alter their consumption behavior (Faruqui et al. 2010). However, this method requires advanced meters because energy suppliers need information about actual driving behavior to schedule a charging process (Goebel 2012).

Despite the promise of controlled charging concepts for both the energy industry and EV users, it is uncertain to what extent the load-shifting potential can actually be used. In this regard, many EV users might not allow any external control on the charging process (Geleen et al. 2013). Moreover, implementing DR requires substantial investment in constructing infrastructure such as energy management systems and smart grid technologies, thus probably diminishing economic benefits (Lyon et al. 2012). From an information management perspective, participation in DR programs for private EV users is challenging because energy suppliers need information about the time and duration that an EV is available for charging (Fridgen et al. 2014).

Designing a Demand Response System for Fleet Operators

In this section, we conceptualize an IS artifact used to determine optimal charging times for an EV fleet without restricting mobility needs. We focus on EV fleets, as they seem to be particularly suitable for a broad implementation of IS-supported DR programs. In this regard, many larger commercial fleet operators have already implemented smart grid and the required ICT technologies (Paulus and Borggrefe 2011). Furthermore, larger energy customers or fleet operators with a sufficient number of EVs can benefit directly from prevailing electricity price fluctuations by purchasing the required energy from the day-ahead spot market for electricity and using it on the next day (Hill et al. 2012).

Our research model is positioned within the energy informatics framework by Watson et al. (2010) which partitions an intelligent energy system into four basic elements:

- A **flow network** represents the transport components (e.g., wiring of power grids) that support or enable the movement of continuous matter (e.g., energy) or discrete objects (e.g., cars). In this study, we focus on a flow network that solely permits the flow of electricity.

- A **sensor network** is a set of connected, spatially distributed devices (e.g., smart meters), whose purpose is report on the status of the flow network. In this study, we consider an AMI that, inter alia, receives and reports data on electricity prices.

- **Sensitized objects** are capable of reporting data about their use. For our case, modern vehicle telematics in the form of data loggers are needed to constantly sense and report the status of the EVs as well as, inter alia, trip information and energy flows to and from the batteries. In addition, load control devices are required for managing the electricity demand, i.e., interrupting the charging process during price peaks.

- The "heart" of the framework is an **information system** that serves as an integrator and ties together the above-described elements. We focus on one of the main functions of IS in the framework, described as "manage supply and demand to avoid high costs resources" (Watson et al. 2010).

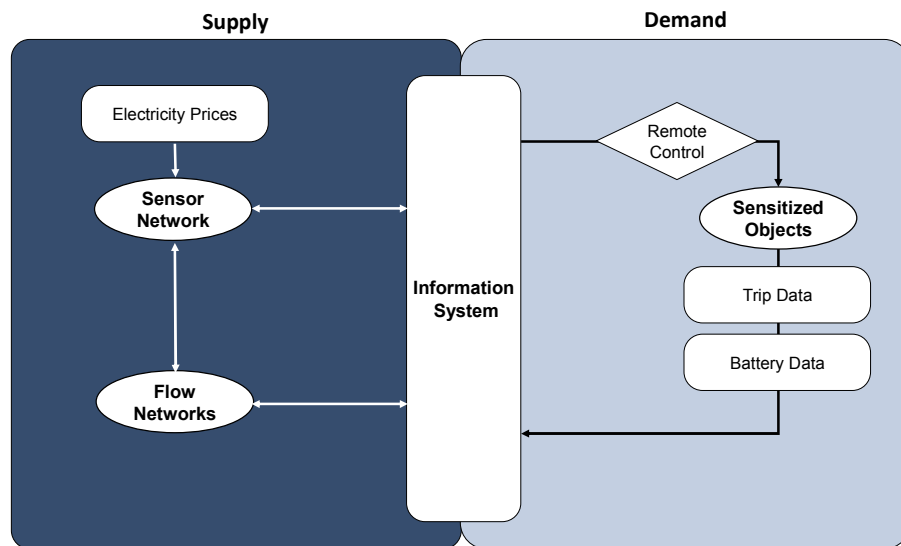Figure 1 illustrates the interactions between all elements within our study.

Figure 1. Embedding the DR Program into the Energy Informatics Framework (adapted from Watson et al. 2010)

Adapting these thoughts, we design an IS to optimize DR decisions for fleet operators using EVs, based on two components: a prediction model and an optimization model. As a necessary precondition for applying DR programs, one must accurately **forecast electricity demand** from the EVs and the DR potential (charging flexibility) for a certain period. Otherwise, an EV might be unavailable due to an insufficient battery status. Surprisingly, most studies investigating the economic profit of smart charging concepts (e.g., Milano and Hersend 2014; Lyon et al. 2012; Schuller et al. 2012; Deilami et al. 2011) do not consider this fact. Information systems can help alleviate this problem by collecting information about EV usage patterns and the battery status; relevant data are detected and reported by sensitized objects and afterwards analyzed. To gather information about mobility requirements, a prediction model based on

historic data is needed for forecasting vehicle use times and energy consumption in a certain period. Thus, the IS requires information on how long the battery must be charged (depending on the current state of charge [SOC] of the battery and distance of the next trip) and when the vehicle is needed again in operation. Furthermore, information on electricity prices is required for a certain period in advance. In Germany, electricity spot market prices can be obtained from the European Energy Exchange (EEX), where hourly prices are determined by day-ahead auctions (Ellersdorfer 2005). Alternatively, fleet operators can receive information about the energy price at a certain time of use from their utility company through AMI.

Using the input data described above, the IS derives **optimal decisions to shift electricity usage** at a given time and thus manages the interdependencies between the supply and demand sides.

Research Methodology

Having described the IS artifact used to apply DR programs for EV fleets, we adapt it for a medium-sized car-sharing operator in Germany. Our pilot case company provides users access to a fleet of 87 company-owned conventional vehicles including 7 EVs. Within the car-sharing operator's business model, the users must pick up and return the vehicles to one of the stations distributed in the operator's area.

Our methodological approach consists of two steps. In the first step, we establish a prediction model forecasting the average hourly distances driven for the EVs considered. As explained in the previous section, it is necessary to forecast the electricity demand of the EVs within a defined time window because the load-shifting potential must be known in advance. The second step involves an economic assessment of applying one DR program (smart charging) to the car-sharing operator's EV fleet. To do so, we perform an optimization of charging costs to reduce energy procurement costs for the pilot case company. The economic assessment of this DR program is based on actual driving profiles of the car-sharing operator's EVs for the reference year of 2014. Additionally, information about the EVs' energy consumption per trip was available, as we constantly monitored and tracked all batteries' SOCs in the reference year.

Prediction Model

To estimate the vehicles' usage, we establish a prediction model forecasting the average distances driven per hour for the K vehicles considered. The resulting electricity demand $d(k, l)$ of one EV k for a certain trip l can be calculated by multiplying the energy consumption per km c by the distance of a certain trip $D(l)$

$$d(k, l) = c \cdot D(l). \tag{1}$$

The data used to establish our prediction model are booking data of the pilot case company gathered within a time frame of $T = 380$ days (05.31.2011–06.30.2012). As the maximum reachable distance of EVs is approximately 120km, we focus on completed tours under this distance. The time frame was subdivided into two intervals. The data from the first interval (300 days, starting on 05.31.2011) are considered as training data, while the second interval's data (80 days, ending on 06.30.2012) are considered as test data. In the first step, we accumulate the distances travelled per one-hour time slot within the training data time frame, which is illustrated for one day and one vehicle in Figure 2. The points represent the exact values and the line a respective maximum likelihood estimation. There is a peak around midday, while in the morning and evening few kilometers were driven.
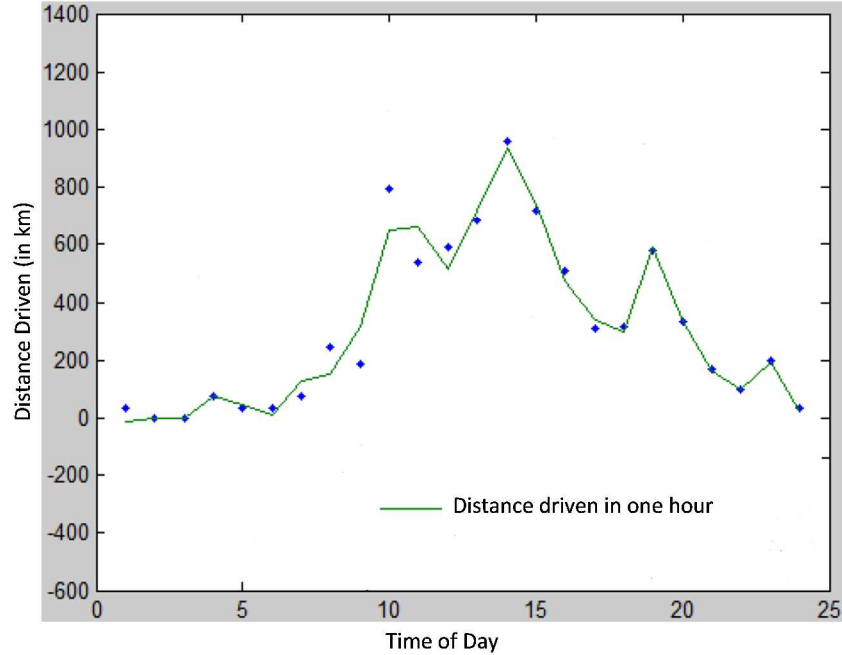
Figure 2. Kilometers Driven for Each Hour of the Day for One Vehicle

Next, we determine the average distances driven per one-hour slot by dividing the accumulated distances by the number of days within the test data time frame. Generally, the consequences of underestimating the future EV demand are worse than those of overestimating. If future demand is underestimated, a trip might not be realized, because the battery is insufficiently charged. To avoid overfitting, an estimator is used (polynomial of degree n), minimizing the distance between the average values and the estimator itself. The polynomial's degree is dependent on the error measure MAPE (mean absolute percentage error); the polynomial with the lowest MAPE is used for the prediction model. To calculate the MAPE, the differences between the estimators $F_{k,t}$ for vehicle k on day t from the training data and the actual values $A_{k,t}$ from the test data are generated for every one-hour time slot (within the corresponding time frame) using

$$\text{MAPE}_i = \frac{1}{T} \sum_{t_{start}}^{t_{end}} \left| \frac{A_{k,t} - F_{k,t}}{A_{k,t}} \right|. \tag{2}$$

Accumulating the modified average values for every one-hour time slot indicates the average distance traveled by a particular time of day, if the vehicle was actually used. To take into account short trends and changes in usage behavior, the prediction model suggested is divided into two parts: a short-term and a long-term component, both weighted with 50%. The short-term component reflects bookings of the last four weeks. In this regard, data from the same weekday and time of day of the previous week is weighted by 50%. Moreover, data from the same one-hour time slot two, three, and four weeks before are considered with weightings of 25%, 12.5%, and 12.5%, respectively. The average distance driven by a particular time of day for one vehicle is illustrated in Figure 3.
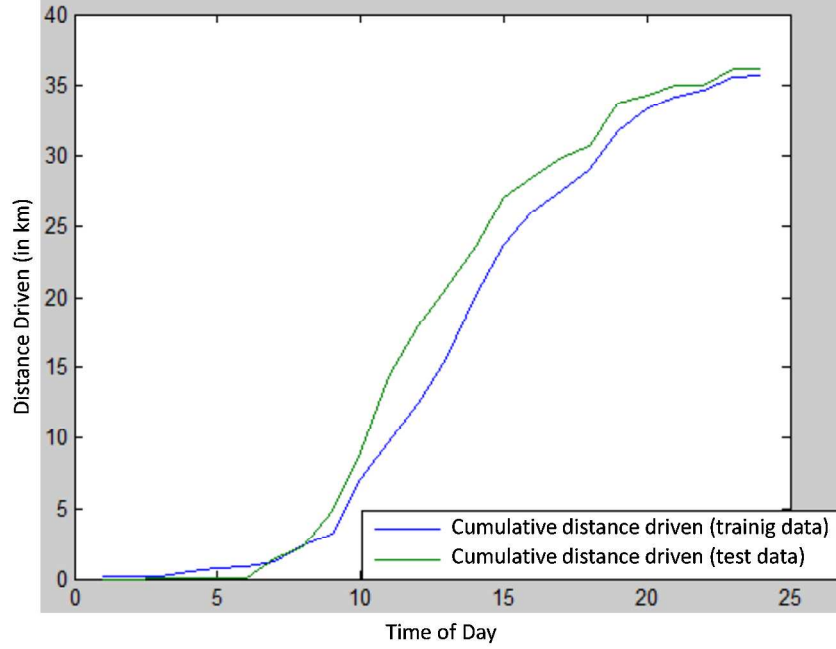
Figure 3. Average Distance Driven until a Particular Time of Day

Our prediction model allows for a forecast of average distances traveled per hour. These values can then be converted into forecasted electricity demand, using Eq. (1). The availability of this information is a prerequisite for applying DR programs for EVs, as explained in the previous section.

Optimization Model

In order to evaluate the results of our optimization approach, we first calculate annual energy procurement costs when charging the EV fleet in an uncontrolled manner (plug-and-charge concept) C_{pnc}. Let d_{Fleet} be the annual electricity demand of the EV fleet and $\bar{p}_{el}$ be the average electricity price for the reference year. To ensure comparability between this charging concept and the smart charging concept, we consider the average wholesale price for the fleet operator as it is the only component of the final retail price that can be influenced by smart charging; the other price components (e.g., electricity taxes or grid fees) are fixed (BDEW 2014). Furthermore, the charging efficiency η is considered by adjusting the demand parameter. Thus, we derive

$$C_{pnc} = \bar{p}_{el}\frac{d_{Fleet}}{\eta}. \tag{3}$$

The application of the DR program for the EV fleet is based on energy procurement on the spot market for electricity. As seen in Figure 4, the electricity spot market exhibits high price volatility and frequent extreme price peaks in Germany. Consequently, the aim is to charge the EVs during the hours with the lowest possible prices.
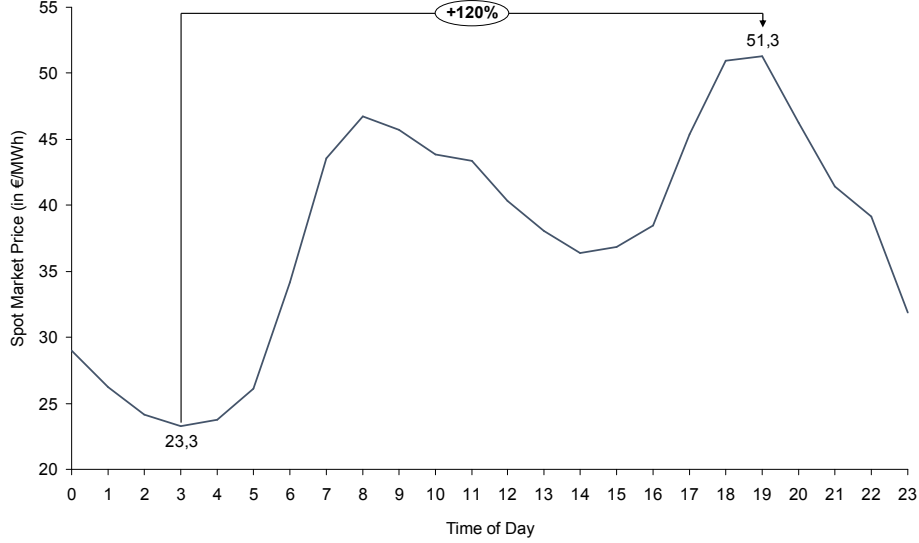
Figure 4. Average Electricity Spot Prices per Hour and Resulting Price Spread in Germany (in 2013)

In the first step of the optimization model, the load-shifting potential per charging process must be defined. For this evaluation, we use historical data from the pilot case company (e.g., tour start and end as well as tour distance) as well as data relating to the charging status $SOC(k, i, t)$ of the EVs' batteries within the reference year. To calculate the electricity demand $d(k, i, t)$ of one EV k in hour i on day t, we use information concerning the maximum battery capacity C_{max} and the charging efficiency η

$$d(k, i, t) = \frac{C_{max} - SOC(k, i, t)}{\text{η}}. \tag{4}$$

The time available for each charging process depends on the idle time between two bookings. Furthermore, let N be the number of minutes necessary to fully charge the battery. This value is dependent on the vehicle's electricity demand $d(k, i, t)$ and the charging power W

$$d\big(d(k, i, t)\big) = 60 \cdot \frac{d(k, i, t)}{\text{W}}. \tag{5}$$

In order to optimize energy procurement costs per charging process, we shift all charging processes to the time slots in which the electricity spot market prices $p_{spot}(i, t)$ are lowest. This is feasible, because electricity spot market prices are determined by day-ahead auctions. In the interest of constraining the charging processes to the hours with lowest prices for electricity procurement, we use the following function as a decision variable

$$H(k, i, t) = \begin{cases} 1 \; for \; charging \; the \; EV \; k \; in \; hour \; i \; on \; day \; t \\ 0 \; for \; not \; charging \; the \; EV \; k \; in \; hour \; i \; on \; day \; t. \end{cases}$$

The car-sharing operator requires that the fulfillment of all booking requests always has priority over reducing charging costs. Therefore, the battery must always be charged sufficiently in order to realize the next trip. The energy procurement costs per charging process $C_{ep}(k, i, t)$ can be calculated by multiplying the electricity demand $d(k, i, t)$ with the spot market prices $p_{spot}(i, t)$ that prevail during the time in which the batteries are charged, under consideration of the decision variable $H(k, i, t)$. The corresponding optimization problem for minimizing energy procurement costs for the whole fleet resolves to

$$\min_{H(k, i, t)} C_{ep}(H(k, i, t)) \sum_{k=1}^{K} \sum_{i=0}^{23} \sum_{t=1}^{365} p_{spot}(i, t) d(k, i, t) H(k, i, t), \tag{6}$$

subject to

$$\sum_{i=0}^{23} H(k,i,t) = N\big(d(k,i,t)\big) \,\forall\, H(k,i,t) \in \{0,1\}; k \in \{1,\cdots,K\}; i \in \{0,\cdots,23\}; t \in \{1,\cdots,365\}.$$

Results

The parameters necessary for assessing the smart charging DR program are presented in Table 1 for the fleet of seven EVs.

Charging strategy	Parameter	Value	Comments	Data source
Plug-and-charge concept	d_{Fleet}	4881	Annual electricity demand of the EV fleet [kWh]	Project data
	η	.90	Charging efficiency	Project data
	p_{el}	7.31	Average electricity wholesale price [€/kWh]	BDEW (2014)
Smart charging	W	11	Charging power [in kW}	Project data
	p_{spot}	[-87.52 − 265.3]	Electricity spot market prices in the reference year [€/MWh]	EEX (2014)
	C_{max}	18.70	Maximum battery capacity (in kWh)	Project data

Table 1. Parameters Used to Economically Assess the DR Program in the Reference Year

The annual costs when charging the EV fleet in an uncontrolled manner with fixed electricity prices can be calculated using Eq. (3) and the parameters listed in Table 1 to be €356.80. It must be taken into account that we calculate annual charging costs using the wholesale electricity price, which is roughly 25% of the retail price for electricity in Germany (BDEW 2014). Therefore, to obtain the consumers' retail prices for electricity, further price components – such as grid fees (5.9 cents/kWh) or apportionments for the promotion of renewable electricity (6.2 cents/kWh) – must also be included. Considering the wholesale price, however, allows for an economic assessment of applying the suggested DR program to the EV fleet.

In this regard, the economic assessment of the smart charging DR program is based on the assumption that the fleet operator procures the required energy on the spot market and charges the batteries during the hours with the lowest possible prices. The optimization approach for one vehicle on an exemplary day is illustrated in Figure 5, in which the trip ends at 2 p.m. with a SOC of 3 kWh. Furthermore, the EV is needed again in operation at 9 p.m. (total charging time available = 7 hours) with a SOC of 15 kWh. Having an available charging power of $W = 11$ kW and a charging efficiency of $\eta = 0.9$, the batteries can be fully charged in 95 minutes. Hence, the charging process takes place during the 1.58 hours with the lowest spot market prices.
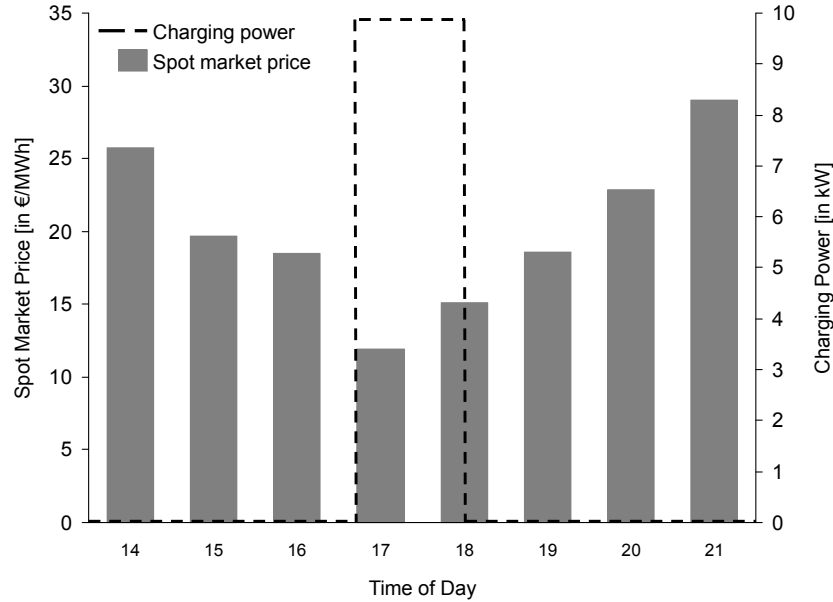
Figure 5. Optimization Procedure for one Charging Process and one EV on a Certain Day

The car-sharing operator can expect significant cost savings when applying the suggested DR program. The annual charging costs were calculated to be €206.50 using Eq. (6).

If the whole 87-car fleet of our car-sharing operator were electrified, the annual cost savings would amount to €1,868 (annual charging costs uncontrolled charging = €4,434 / annual charging costs smart charging = €2,566).

Discussion

Our analysis is based on a business case with a car-sharing operator in Germany. Nevertheless, our suggested IS design for applying DR to EV fleets can be adopted by all kinds of companies with characteristics similar to those of our pilot case company, including logistics providers, parcel delivery firms, or outpatient nursing services. As part of the IS, a prediction model was used to forecast the vehicles' usage times and energy consumption. This information is a prerequisite for deriving the optimal decision to shift demand at a given time. Precise predictions for upcoming but not already executed bookings are particularly important for car-sharing providers applying DR because incorrect predictions of EV demand may lead to additional costs. In this context, it must be noted that the main goal of a car-sharing operator is to fulfill all booking orders rather than optimizing energy procurement costs.

Using an optimization approach, we demonstrated that fleet operators can expect significant cost savings when applying DR programs for their EV fleets. Within our suggested DR program, charging processes are interrupted during spot market price peaks and shifted to the hours in which the spot market prices are the lowest. This results in cost savings of at least 42% in comparison to a simple plug-and-charge approach. Thus, applying DR programs has the potential to make EV fleets economically sustainable, as the already existing operational cost advantage can be further increased. Furthermore, fleet operators using EVs can expect reputational benefits from adopting eco-friendly technology. The combination of these aspects could promote the market penetration of EVs, thereby supporting the government's objective of reducing transport emissions. In particular, the electrification of car-sharing vehicles offers great environmental potential, as almost 0.5 million people used car-sharing services regularly in Germany in 2014 (IfD Allensbach 2014), and it can only be assumed that the number of users will increase.

The DR program presented is also associated with energetic benefits. It is generally known that charging a large number of EVs in an uncontrolled manner is likely to jeopardize the security of energy supply

because of an expected increase of peak load. This can be avoided by shifting charging times into time ranges in which electricity prices are low. Because electricity prices are particularly low when a large amount of renewable energy is available or electricity demand is low, the DR program would also indirectly promote the development of renewable energies. The German government's intention to increase the share of renewable energies (BMWi and BMU 2010) influences DR programs in two ways. Discrepancies between power supply and demand can be expected to increase, which means that this DR program could make an important contribution to enhancing the security of energy supply. Furthermore, price volatilities on the spot market are also likely to increase (Ketterer 2014), which would have a positive effect on the profitability of this DR program.

Our study contributes to IS research in three major ways. First, we appear to be the first to investigate how smart charging programs can be applied for fleet operators under realistic conditions. To do so, we conceptualized a comprehensive IS artifact that can be adopted by other companies using EVs. Second, we followed the call by Watson et al. (2010) and Dedrick (2010) by contributing to the research stream of energy informatics. In this regard, our approach helps to increase energy efficiency and match supply and demand in the grid. Third, our approach can contribute to assessing the economic value of IS-supported DR programs (Strüker and van Dinther 2012).

However, the following limitations should be considered. As the investigation is based on a case study, the results cannot be expected to be representative for all kinds of users. Furthermore, we assumed that the fleet operator itself can act on the spot market. Under current energy market conditions, however, an intermediary offering access to the energy stock is required. Alternatively, a utility company can offer time-variable electricity tariffs, but both approaches would diminish the economic benefits. Finally, we established a prediction model to forecast the electricity demand of an EV. However, it is challenging to precisely predict future trips based on historical driving patterns, particularly if the EVs are used at irregular intervals.

Conclusion

In this study, we designed an IS artifact that can be used by fleet operators to apply DR programs for battery charging based on two components: a prediction model and an optimization model. Using real-world data from a car-sharing operator that uses EVs, we demonstrated that fleet operators can expect significant cost savings when applying DR programs for their EV fleets. Applying DR programs for EVs can thus make a valuable contribution to ensuring that these vehicles become economically competitive. This finding is significant because it addresses one of the main barriers of EV adoption, i.e., their significantly higher purchasing prices in comparison to conventional vehicles. Along with economic benefits, the implementation of controlled charging concepts also brings energetic benefits as DR promotes the development of renewables. However, the application of DR programs currently faces barriers, as most EV users have a limited understanding of the benefits of DR solutions. As our study revealed the potential for significant cost saving through the use of DR, this might convince further companies to adopt DR solutions.

Summarizing, we illustrated how IS research can foster sustainable development. Given the rapid expansion of renewable energies it is important that in the future smaller, flexible consumers participate in DR and respond to the intermittent supply of energy. From a fleet operator's point of view, DR seems compelling because energy procurement costs can be reduced by, for example, adjusting the time of energy usage. A useful extension of this work is to investigate the application of DR programs in further areas of applications, such as at logistics providers. Further, our IS must be expanded in future so that car-sharing users can supply information on future trips. This would increase the forecast reliability of EV energy demand for a certain period and thus facilitate the application of DR programs for EV fleets.

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