About business model specifications of a smart charging manager to integrate electric vehicles into the German electricity market

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Abstract

In order to reach greenhouse gas emissions reduction targets, electric vehicles have been discussed as an energy-efficient and climate-friendly means of individual transportation. One of the open questions is how electric vehicles can be integrated in electricity markets in an intelligent fashion. One option is that a new type of aggregator, a so-called smart charging manager, is contracting households and manages the charging of their electric vehicles. This aggregator considers the available load shifting potential and current price signals from electricity markets. In this paper, basic steps are undertaken to analyse the business model of such an entity.

Based on a survey of French and German users of electric vehicles and respondents who had not yet used electric vehicles, a binary logistic regression model is fitted in order to assess the probability of buying electric vehicles based on responding households' income levels, experience with electric vehicles, car usage frequency, daily mileage as well as number of cars they have in their households. This model can be used to assign probabilities of electric vehicle adoption to households of a representative mobility survey in Germany. In a next step, an electric vehicles diffusion scenario is developed which allows deriving the number of electric vehicles in Germany on a yearly basis until 2030. Considering that purchase intentions for electric vehicles as well as mobility patterns are known for individual households representative for Germany, corresponding electricity demand as well as load shifting potentials are determined. On this basis, potential revenues of a smart charging manager from smart tariffs and the effects on electricity markets are analysed. For the latter, the additional flexible electricity demand induced by electric vehicles and the smart charging manager as a new aggregator agent are implemented in the agent-based simulation model PowerACE for the German wholesale electricity market. The smart charging manager's role in the model is to maximize its profit in the day-ahead market based on the tariff structure and the available load shifting potential. For the analyses, profitability is assessed for three charging scenarios varying in the load shifting flexibility (0 %, above 50 % SOC and complete flexibility) available for the smart charging manager and for two selected years, 2022 and 2030.

Results indicate that the smart charging business model could be profitable in general as contribution margins are positive in the considered scenarios and years. However, the yearly contribution margin in selected years is decreasing in the load shifting scenarios. Managing the charging of electric vehicles can be beneficial from a pure cost perspective as costs for purchasing electricity on the day-ahead market are lower. But the smart charging manager's cost reductions may not outweigh the lower revenues generated by the smart charging tariffs due to the customers' lower willingness to pay during the times they offer their load shifting potential to the smart charging manager.

Future research includes integrating stochastic aspects in the electric vehicles diffusion model, enlarging the survey to evaluate electric vehicle owner's willingness to pay for smart charging tariffs as well as an extended scheduling algorithm of the smart charging manager when bidding in electricity spot markets.

Introduction

The European and German target of reducing greenhouse gas emissions by 80 % by the year 2050 (European Commission 2011; Bundesregierung 2010) will require changes in the transportation sector as today it accounts for about 23 % (18 %) of the total European (German) emissions (Eurostat 2013). Furthermore, the share in Europe has considerably increased since 1990 (Eurostat 2013). As individual road transportation is responsible for the main share of those emissions (Eurostat 2013) and fossil fuels seem to have no alternative yet, significant changes of powertrains and fuels seem to be unavoidable (cf. Kay et al. 2013).

Electric vehicles (EV) have been discussed as a more energy-efficient and climate-friendly means of individual transportation. Due to positive developments in the battery technology (Thielmann et al. 2012), battery electric vehicles are experiencing a comeback in recent years. Currently, around 40 different EV are offered on the German market (Eckl-Dorna

& Sorge 2013) while 12,156 cars have been registered on January 1st, 2014 (KBA 2014). Considering that the majority of forecasts for EV diffusion in Europe (cf. Kay et al. 2013) assume that EV will become an important powertrain alternative, the future electricity demand from these vehicles will increase considerably. Without managing this demand, it will predominantly occur during peak evening hours (e.g. Jochem et al. 2012). The implementation of smart charging and load management of EV might be, from a technical point of view, straightforward as all current battery electric vehicles and most public charging stations already communicate according to the ISO15118 standard. This communication interface allows an exchange of all necessary information for shifting the charging process in time without affecting the vehicle users' requirements. Furthermore, as cars are commonly not used during the night, their charging could be shifted into these off-peak night hours if plugged-in. Given lower spot electricity prices during off-peak hours and substantial technical load shifting potential (cf. Babrowski et al. 2014), a business model focusing on a smart charging manager could emerge. In this paper, such an entity operating as a new type of electricity supplier is analysed. It aggregates individual electricity load profiles from EV and manages the charging processes of these EV in a profit maximizing way while considering spot prices of electricity and individual user needs with regard to EV availability.

The paper is structured as follows. Initially, the diffusion of EV in Germany until 2030 is estimated. EV purchase probabilities for German households at different points of time are determined with the support of a Bass Diffusion Model (Bass 1969) and calibrated with survey data from 180 EV users. In a next step, individual trip profiles using EV based on microdata from a mobility survey representative for Germany form the basis to determine load shifting potentials during the charging process of EV. Subsequently, the role of a smart charging manager exploiting the households' load shifting potentials is introduced. General specifications of the business model are presented and the aggregator is implemented in the agent-based simulation model PowerACE for the German wholesale electricity market. The profitability of variants of such a business model is assessed by simulating the smart charging managers' load-scheduling and load shifting activities for three different charging scenarios in 2022 and 2030. Finally, conclusions from the presented results are drawn.

Methods used

Modelling diffusion of electric vehicles

According to the Bass Diffusion Model (cf. Bass 1969), diffusion of innovations depends on the interaction between current and potential adopters, called innovators and imitators. In the Bass Diffusion Model, imitators and innovators are represented by an imitation *(p)* and an innovation *(q)* coefficient. The Bass Diffusion Model further depends on the market potential *m*. The number of cumulated adoptions until time *t* is represented by the following equation:

$$N(t) = m\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}$$

As German EV stock history (cf. KBA 2014) as well as the German government's objectives concerning EV stock in 2030 are known, the equations parameters for the innovation and imitation coefficient can be assessed for an optimistic scenario under the assumption that in the long-term all vehicles will be replaced with EV and the national objective is achieved in 2030. This is done with the support of nonlinear regression methods.

As for later analyses not only the number of adoptions is of major interest, it needs to be assessed who will adopt EV. This is done by applying the binary logit model presented in Ensslen et al. (2015) assessing EV purchase intentions based on stated preference data originating from 180 survey participants who have partly already had first experiences with EV. This model is used to assign probabilities of EV adoption to households from a representative mobility survey in Germany ("Mobilität in Deutschland"; cf. MiD 2010). Households' probabilities of replacing their cars are determined by the following binary logistic regression model: $P(y=1) = \frac{1}{1+e^{-l_i}}$

$$l_i = -1.567^{*} + 0.691x_1^{\circ} + 2.079x_2^{*} - 0.349x_3 - 0.970x_4 - 0.706x_5 + 0.600x_6 + 0.097x_7 + 2.062x_8^{**} + 0.649x_9 + 0.587x_{10}^{*} + \varepsilon_i$$ [1,2,3,4]

[1] Significance level of Wald statistic: °: p<0.1; *: p<0.05; **: p<0.01; ***: p<0.001.

[2] Reference category for dichotomized variables x_3 and x_4: Respondent has experienced EV during several trips. Wald Test Statistic: $T_W^2 \sim \mathrm{X}^2$=4.709; df=2; p=0.095.

[3] Reference category for dichotomized variables x_5 and x_6: Respondent did not want to provide information about the households' net income. Wald Test Statistic: $T_W^2 \sim \mathrm{X}^2$=8.701; df=2; p=0.013.

[4] Reference category for dichotomized variables x_7 and x_8: Car usage frequency: (Almost) daily. Wald Test Statistic: $T_W^2 \sim \mathrm{X}^2$=7.244; df=2; p=0.027.

with:
y: Dependent variable representing potential EV purchase intention within the next years (0: Negative or Undecided / 1: Positive)
x_1: Travelled mileage on a (work)day (0: $< 50\ km$ / 1: $\geq\ 50\ km$)
x_2: Fleet manager and user (0: No / 1: Yes)
x_3: Respondent has experienced EV during one or two trips as a driver or passenger (0: No / 1: Yes)
x_4: Respondent has not experienced EV so far at all (0: No / 1: Yes)
x_5: Net household income < 4,000 € (0: No / 1: Yes)
x_6: Net household income ≥ 4,000 € (0: No / 1: Yes)
x_7: Car usage frequency: 1-3 days per week (0: No / 1: Yes)
x_8: Car usage frequency: 1-3 days per month or less (0: No / 1: Yes)
x_9: French respondent (0: No / 1: Yes)
x_{10}: Number of cars in the household (0-4 if $x_{10} \leq 4$ / 5 if $x_{10} > 4$)

As in the year 2012 only a very low share of the German population (i) has been users of EV as well as (ii) fleet managers, the variable x_2 has been set to 0. Furthermore, only a very small share of the German population has probably had the possibility to perform test drives with EV in 2012, as not many EV have been on the market back then. Accordingly, x_3 has also been set to 0 and x_4 to 1. As the used dataset is derived from a representative survey for Germany, x_9 is set to 0. These assumption lead to the following logit function:

$$l_i = -2.537^{*} + 0.691 x_1^{\circ} - 0.706 x_5 + 0.600 x_6 + 0.097 x_7 + 2.062 x_8^{**} + 0.587 x_{10}^{*} + \varepsilon_i$$

On this basis, a probability of buying an EV within the next years $P(y = 1)$ is assigned to all simulated German households. Based on these probabilities, the vehicles in households replaced by EV in the future can be identified in the following manner:

$$N(\tilde{t}) = \sum_{i \in M} w_i \cdot 1_{[l_i > \mu_{\tilde{t}}]} = |M_{\tilde{t}}|$$

with $\mu_{\tilde{t}}$ being the smallest $l_i \in M_{\tilde{t}}$, so that $\sum_{i \in M} w_i \cdot 1_{[i \in M_{\tilde{t}}]} = N(\tilde{t})$

with:
$t \in T = \{0,1,2, \dots, \tilde{t}, \dots, T_{max}\}$
M: Set of vehicles in the MiD
$M_{\tilde{t}} \in M$: Vehicles substituted by EV by time $\tilde{t}$
w: Weighting factor to make the MiD' households representative for Germany

Considering that EV purchase intentions as well as corresponding mobility patterns are known for individual households representative for Germany, corresponding electricity demand as well as load shifting potentials of individual households can be determined and aggregated.

Specification of the smart charging manager's activities

A smart charging manager can be defined as a smart charging service provider offering households with EV the option to have their load shifted to off-peak hours, so that charging becomes cheaper for the consumers. According to Dütschke and Paetz (2013) utilities should provide simple programs in the sense of being transparent and predictable, i.e. with little dynamics. Accordingly, the following tariff is constructed incorporating the issues mentioned above of being simple (i), as during a charging process only two price levels occur and of being transparent and predictable (ii), as all parameters are fixed and known to the customers correspondingly before the charging process is started. Furthermore, the tariff introduced here incorporates answers to a range of specific concerns linked to load shifting activities (cf. Krems et al. 2011). After being plugged in, the EV is directly charged to a particular level required by the customer (e.g. for cases of urgencies) and the smart charging manager guarantees that the EV is completely charged the next time it is expected to be needed. Formally, this tariff can be described as:

$$p_i(t) = \begin{cases} p_{max} & , \quad t_{0,i} < t \leq t_{1,i} \\ p_{min} + \left((p_{max} - p_{min}) \left(1 - \frac{min(t_{LSP,i},\ T)}{T} \right) \right) & , \quad t_{1,i} < t \leq t_{2,i} \end{cases}$$

The time available to the smart charging manager for load shifting activities, i.e. the period the EV is plugged in, but no charging is required to take place, is defined as $t_{LSP,i}$ and is calculated as follows:

$$t_{LSP,i} = (t_{2,i} - t_{1,i}) - \frac{W_{SOC_i,t_{2,i}} - W_{SOC_i,t_{1,i}}}{P_{max}}$$

The parameter T is defined by the smart charging manager and represents the minimal flexible time for load shifting activities provided by a customer to the smart charging manager so p_{min} is paid between $t_{1,i}$ and $t_{2,i}$ (customer i will pay p_{min} if $t_{LSP,i} > T$).

with:
W_{SOC_i}: State Of Charge (SOC) of the battery [kWh]
P_{max}: Maximum charging power an EV can be charged with [kW]
i $\in \{1, \dots, N\}$: Customers of the smart charging manager
$t_{0,i}$: Point in time when the EV is connected to the grid
$t_{1,i}$: Point in time when the smart charging manager can start load control charging activities (dependent on the user requirements)
$t_{2,i}$: Point in time when the battery is supposed to be fully charged

Figure 1 illustrates how a potential charging process with load control by the smart charging manager and corresponding price levels could look like. Furthermore, the smart charging manager's optimization potential in order to maximize profit is illustrated (dotted rhomboid).

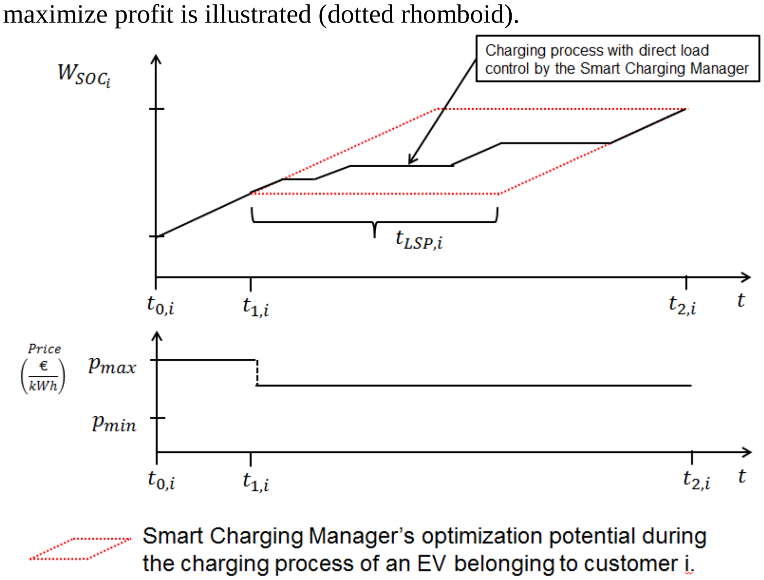

Figure 1: Illustration of the charging process with load control by the smart charging manager

Measuring willingness to pay for the smart charging manager's tariff

In order to analyse the acceptance of the presented tariff, a survey has been conducted comparing this tariff to a conventional single price level tariff. In order to determine the potential revenues of a smart charging manager, the willingness to pay (WTP) has been measured by applying the Van Westendorp method (cf. Van Westendorp 1976, Reinecke et al. 2009). Using this method is appropriate, because WTP for an innovative service where price references do not yet exist need to be assessed (cf. Reinecke et al. 2009). Based on directly interviewing potential customers, four price levels are determined representing the individuals' price perceptions for a product being (i) cheap, (ii) expensive, (iii) too expensive, (iv) too cheap.

Based on these four price levels different cumulated frequency distributions and inverted cumulated frequency distributions are visualized in one diagram in order to determine the product's following prices:

(i) The optimal price: It represents the price where consumers' resistance against purchasing the product is lowest. This price represents the product's price where the same number of respondents state the product to be too expensive as to be too cheap.

(ii) The indifference price: It provides information about the consumers' price sensitivities. The closer the indifference price and the optimal price are, the more price sensitive are the consumers. It is represented by the price where the same number of consumers states that the product is expensive as to be cheap.

(iii) The acceptable price range is represented by the product's "marginal cheapness" and the product's "marginal expensiveness". At the price representing a product's marginal cheapness the same amount of respondents state a product to be too cheap as there are respondents providing information about a product of not being cheap. At the price of marginal expensiveness the same number of respondents states that a product is too expensive as there are respondents providing the information about a product of being not expensive.

Simulation of the smart charging manager's activities on the German wholesale electricity market

In a next step, the smart charging managers' role as an aggregator of electricity demand from EV in the German wholesale electricity is addressed. An agent-based simulation model is used in order to estimate the costs of purchasing the electrical energy required to charge the EV and to assess the influence on the smart charging manager's business model. In general, agent-based simulation is an appropriate framework for analysing electricity markets and interactions therein. The agent perspective allows implementing different characteristics and strategies of market participants[5].

The analysis is conducted on the basis of the existing agent-based electricity market model PowerACE which simulates the main participants in the German wholesale electricity market with a focus on the day-ahead market (e.g. Genoese et al. 2012). The model results include, amongst others, hourly market clearing prices for all simulated years. The main input data for the simulation of the German electricity market (e.g. power plants, demand) is based on the scenarios in Ringler et al. (2014). In order to integrate the effects from the diffusion and charging of EV in Germany until 2030, a smart charging manager is introduced as a new agent in the model. The smart charging manager acts on one side as a demand aggregator and on the other side as a trader on the simulated day-ahead market. The agent aims to maximize its profit by exploiting the available load shifting potential based on the tariff structure and day-ahead price dynamics.

For the simulation of the wholesale electricity market it is assumed that there is only one smart charging manager in each market area managing the charging of all EV. The agent's activities are based on the data and diffusion model described above which is updated and integrated in the simulation model on a yearly basis. The energy volume managed by the smart charging manager is therefore equal to the total energy demand from EV in Germany.

The smart charging manager can operate in different modes according to the tariff structure. In the simplest scenario ("Direct charging"), the households with EV do not enter into flexible contracts. Thereby, the smart charging manager cannot shift the charging of the vehicles to off-peak hours. In this case, the smart charging manager simply aggregates the static load curve of the EV based on their diffusion as well as the assumed mobility behaviour of the households. This static load profile is subsequently bid in the day-ahead market.

In more advanced scenarios, the smart charging manager can use the flexibility to shift the charging to hours with lower expected electricity prices according to the guaranteed SOC of the battery demanded by the households. Two scenarios will be analysed: one with a guaranteed SOC of 50 % ("Flexible charging 50 %") and one with full flexibility for the smart charging manager ("Only flexible charging"). The algorithm for generating day-ahead bids in such scenarios comprises different steps. Initially, the smart charging manager generates endogenously on each day a price forecast for the 24 hours of the following day. The forecast is based on a merit order model of the respective market area using the information available to the agent. On the demand side, the expected consumption of EV is included based on the expected static profile without load shifting. In order to maximize its profit, the agent uses the price forecast and shifts the charging of the EV into hours with low prices. The total load shifting potential is given by a combination of different factors. The guaranteed SOC allows the smart charging manager to shift parts of the charging energy at its own discretion, e.g. a guaranteed SOC of 50 % means that half of the battery's capacity needs to be charged as fast as technically possible and that the other half can be charged according to the smart charging manager's algorithm. The potential is furthermore determined by the expected usage of the EV including consumption as well as start and end times of daily trips[6]. The maximum charging power of 3.7 kW is an additional technical limitation. Within these different limits the smart charging manager generates an optimized load profile for each EV under contract. The price forecast is identical for all EV considered and there is no consideration of any price effects of the smart charging manager's bids within the scheduling algorithm. Finally, the load profiles of all EV are aggregated for the day-ahead bids.

The day-ahead bids are submitted as price-independent bids. Thereby, the simulated smart charging manager ensures that the demand from the EV can be procured on the day-ahead market. Since it is assumed that the smart charging manager

[5] See, for instance, Tesfatsion (2006) and Weidlich and Veit (2008) for a more detailed introduction to the use of agent-based simulation techniques for electricity market models.

[6] The smart charging manager does only manage the charging at home, i.e. the agent cannot exploit any load shifting potential when the EV is not parked at home. Typically, vehicles are used during the day which reduces the available load shifting potential in this period.

has perfect information with regard to the day-ahead demand of the households' EV, there is, furthermore, no need to adjust the schedule before physical delivery (e.g. on an intraday market).

Through the participation of the smart charging manager in the day-ahead market the effects from the additional demand of EV on wholesale electricity prices can be analysed in general and the smart charging manager's costs for purchasing the required electricity in specific.

Results

Diffusion of electric vehicles in Germany until 2030

The EV diffusion scenario used in this paper has been determined by fitting EV stock data (cf. Figure 2, KBA 2014) for the years 2009 until 2013 as well as the German government's goal of having at least 5 million EV on German roads in 2030 (Bundesregierung 2009) by using the Levenberg Marquardt iteration algorithm in OriginLab's OriginPro 9.1 for non-linear curve fitting of the equation

$$N(t) = 43.9 \cdot 10^6 \cdot \frac{1-e^{-(p+q)(t+x)}}{1+\frac{q}{p}e^{-(p+q)(t+x)}}.$$

The curve fitting algorithm determined the parameters $p = 1.922 \cdot 10^{-5}$, q=0.352, x=2007.945. The diffusion of EV in Germany on a yearly basis is shown in Figure 2. The diagram on the left hand side visualizes the German EV diffusion forecast until 2020. The diagram on the right hand side provides information about the deviations between the model and EV stock in Germany at the end of the years 2009 until 2013.

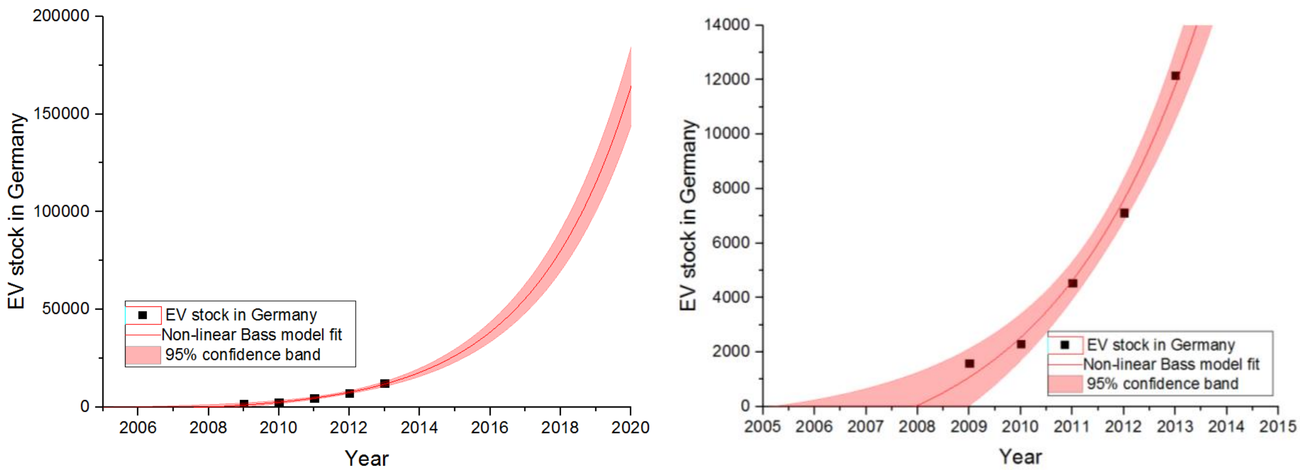

Figure 2: Diffusion of EV in Germany

As the first EV powered by lithium-ion accumulators have been launched on the US market in 2008 (cf. Tesla Motors Inc. 2008) and the first Tesla roadster has been sold in Germany mid of 2008, having no EV on German roads in the year 2008 can be justified. Furthermore, the EV diffusion scenario until 2030 represented by this equation can be justified as it is in line with the German government's goal from 2009 of at least 5 million EV on German roads in 2030. On a first glance, this model seems very good with R^2=0.99998. But it has been estimated by using only six data points, one of them even representing a future objective. Correspondingly, uncertainties are high. In this paper, the points in time 2022 and 2030 are of particular interest. According to the model 332,887 EV will be on the German market in 2022 and about 5 million in 2030.

Revenues of the smart charging manager

The WTP of two different EV specific charging tariffs has been measured based on a survey with about 70 survey participants. About ⅔ of them are between 20 and 30 years old. About ⅔ of the respondents are male. About 40 % of the survey participants have a master degree, about 25 % a bachelor degree and about 25 % a diploma from German secondary school qualifying for university admission or matriculation. As many of the survey participants are students, about 40 % of the survey participants have a household net income level below EUR 1,000. Application of the van Westendorp method permitted to derive the following prices shown in Table 1.

Table 1: Willingness to pay for EV charging with two different tariffs

Tariff	Period the corresponding price levels are applied	(i) Optimal price [EURct/kWh]	(ii) Indifference price [EURct/kWh]	(iii) Acceptable price range [EURct/kWh]	Diagram
Single price level tariff	Direct charging between $t_{0,i}$and $t_{2,i}$	20	22.6	15.2 – 33.4	Cf. Figure 5
Two price level tariff	Direct charging between $t_{0,i}$ up to the users' SOC comfort level at time $t_{1,i}$	21.9	25.2	14.7 – 32.1	Cf. Figure 6
	Charging process is managed by the smart charging service provider between $t_{1,i}$ and $t_{2,i}$	14.3	19	11.2 – 28.0	Cf. Figure 7

Knowing that today's electricity prices paid by the consumers in Germany are above the optimal prices presented in Table 1, the optimal prices for the two price levels of the smart charging tariff are only used to determine the relative WTP for the two level smart charging tariff presented above compared to a single price level tariff. Correspondingly the survey participants are willing to pay 9.5 %[7] more for directly charging their EV up to a certain SOC comfort level when using the two price level smart charging tariff presented above. As the direct charging option represents a service delivering additional utility to the customers, additional WTP compared to the smart charging tariff without the direct charging option up to a particular SOC is coherent.

On the other hand, they are willing to pay 28.5 %[8] less during the time they hand over the control of the charging process to the smart charging service provider.

The smart charging manager's revenues are calculated the following way. In 2013, German households with three persons paid on average 28.84 EURct/kWh for their electricity (BDEW 2013). About 30 % of this price is due to electricity generation (wholesale prices and retail costs) (BDEW 2013) which essentially constitutes the smart charging manager's specific revenues from its customers. These revenues need to cover respective costs for purchasing electricity on the wholesale market and for retailing activities in order to operate in a profitable manner.

In the smart charging business model variant presented here T is set to a very short time bigger than 0. Accordingly the smart charging manager's tariff offered to the EV using customers has the following structure:

$$p_i(t) = \begin{cases} p_{max}\ , & t_{0,i} < t \leq t_{1,i} \\ p_{min}\ , & t_{1,i} < t \leq t_{2,i} \end{cases}$$

Accordingly, the revenues for one EV of the smart charging manager have the following structure:

$$r_i(t) = \begin{cases} (1 + 9.5\ \%) \cdot 28.84 \dfrac{ct}{kWh} \cdot 0.3 = 9.474 \dfrac{ct}{kWh}, & t_{0,i} < t \leq t_{1,i} \\ (1 - 28.5\ \%) \cdot 28.84 \dfrac{ct}{kWh} \cdot 0.3 = 6.186 \dfrac{ct}{kWh}, & t_{1,i} < t \leq t_{2,i} \end{cases}$$

Aggregating the revenues of the charging processes of the EV for the year $\tilde{t}$ can be explained with the following equation:

$$R_{M_{\tilde{t}}} = 365 \cdot \sum_{i \in M_{\tilde{t}}} \sum_{t \in \{t_{0,i},\dots,t_{2,i}\}} w_i \cdot 3.7kWh \cdot 1_{[l_i > \mu_{\tilde{t}}]} \cdot r_i(t) \cdot \begin{cases} 3.7kWh & , W_{SOC_{i,t}} < 16.3\ kWh \\ 1 - W_{SOC_{i,t}}, & W_{SOC_{i,t}} \geq 16.3\ kWh \end{cases}$$

Based on the logistic regression model presented above, probabilities of purchasing an EV are assigned to households. The point in time when individual households become EV adopters and replace their conventional cars are determined by the logit scores. Households showing the highest logit scores are assumed to be the first ones replacing their conventional

7 $\dfrac{21.9 \frac{ct}{kWh} - 20 \frac{ct}{kWh}}{20 \frac{ct}{kWh}} = 9.5\ \%$

8 $\dfrac{14.3 \frac{ct}{kWh} - 20 \frac{ct}{kWh}}{20 \frac{ct}{kWh}} = 28.5\ \%$

cars with EV. Cars of households with lower logit scores are replaced by EV later. In combination with the Bass Diffusion Model presented above the number of EV on German roads in a particular year is determined. The logit scores define the order of the households replacing their cars with EV and, thereby, the composition of sampled EV.

As the kilometres travelled are known for each car from the used database, the energy consumed by the cars having been replaced by EV is calculated based on the assumption that all EV have a battery with a capacity of 20 kWh permitting to travel 100 kilometres. Projecting the daily EV specific energy demand for the year 2030 results in an annual total EV specific electricity consumption of 8,244.7 GWh (about 2 % of total national demand). Based on this consumption revenues are calculated for the three different scenarios (Table 2).

Table 2: Smart charging manager's revenues in 2022 and 2030 in the three different scenarios

Year	Annual total consumption (GWh)	Direct charging [EURmn]	Flexible charging 50 % [EURmn]	Only flexible charging [EURmn]
2022	419.1	36.3	31.3	25.9
2030	8,244.7	713.3	597.5	510.0

Direct costs of smart charging manager for purchasing electricity

In order to estimate the costs of the smart charging manager to purchase electricity required for charging the EV on the electricity spot market, the development of the German wholesale electricity market is simulated using the PowerACE model including the extensions described above.

The diffusion and charging of EV in Germany results in an increase of total system load in future years. Based on the estimated diffusion model and mobility data, Figure 3 shows how the charging of EV affects the aggregated average daily load curve in Germany in 2030 depending on the different charging scenarios. If the charging process is not managed, there is a particular increase of system load in the evening hours. In the other two scenarios, the new load is gradually shifted in night hours. During the day the load shifting potential is marginal because most EV are not available for charging in these hours based on the underlying mobility data.

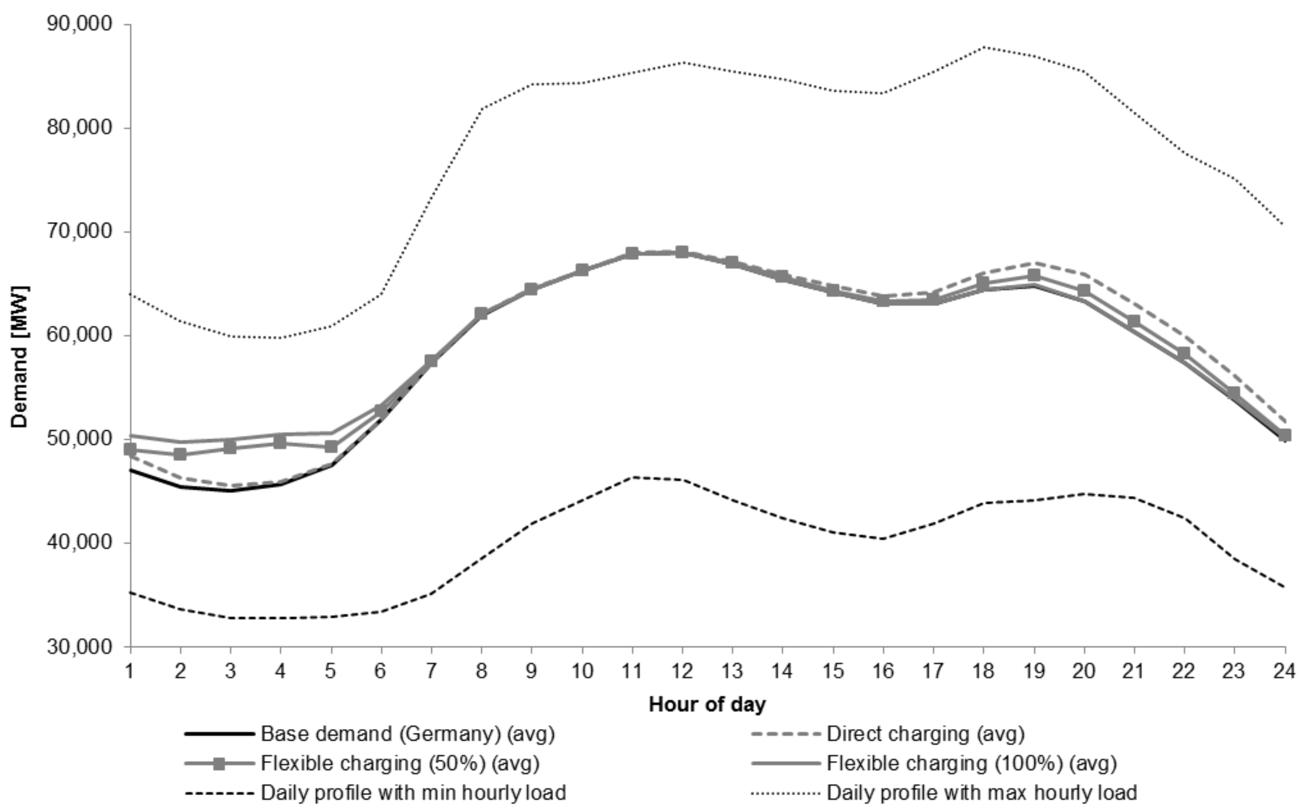

Figure 3: Aggregated, average hourly electricity demand in Germany in 2030 in considered charging scenarios

Depending on the different charging scenarios, the smart charging manager can profit from the available load shifting potential by shifting the charging of EV in hours with lower prices compared to peak evening hours. In Table 3 the yearly costs of the smart charging manager for purchasing electricity on the day-ahead market are shown. As expected, the higher the flexibility of the smart charging manager, the lower the costs. Furthermore, this effect is increasing over the years given the growing load shifting potential in absolute terms. However, in later years two opposite effects can occur in parallel. On the one hand, the smart charging manager can effectively avoid hours in which prices are expected to be high. Mainly evening peaks are avoided because load shifting potential is only marginal during the day. On the other hand, the smart charging manager evolves with its growing trading volume from a pure price taker to an agent directly influencing market clearing prices in some situations. While in the scenario with direct charging, again prices in the evening hours are affected, this price effect caused by the smart charging manager is deferred to night hours in scenarios with load shifting. Figure 4 shows that in the load shifting scenarios prices increase in night hours compared to the static scenario. Such effects are not considered in the smart charging manager's scheduling problem and are discussed again below in the context of the paper's limitations.

Table 3: Costs for purchasing electricity on the day-ahead market in considered charging scenarios

Year	Trading volume (GWh)	Direct charging [EURmn]	Flexible charging 50 % [EURmn]	Only flexible charging [EURmn]
2022	419.1	15.5	14.0	12.9
2030	8,242.2	419.1	357.2	337.0

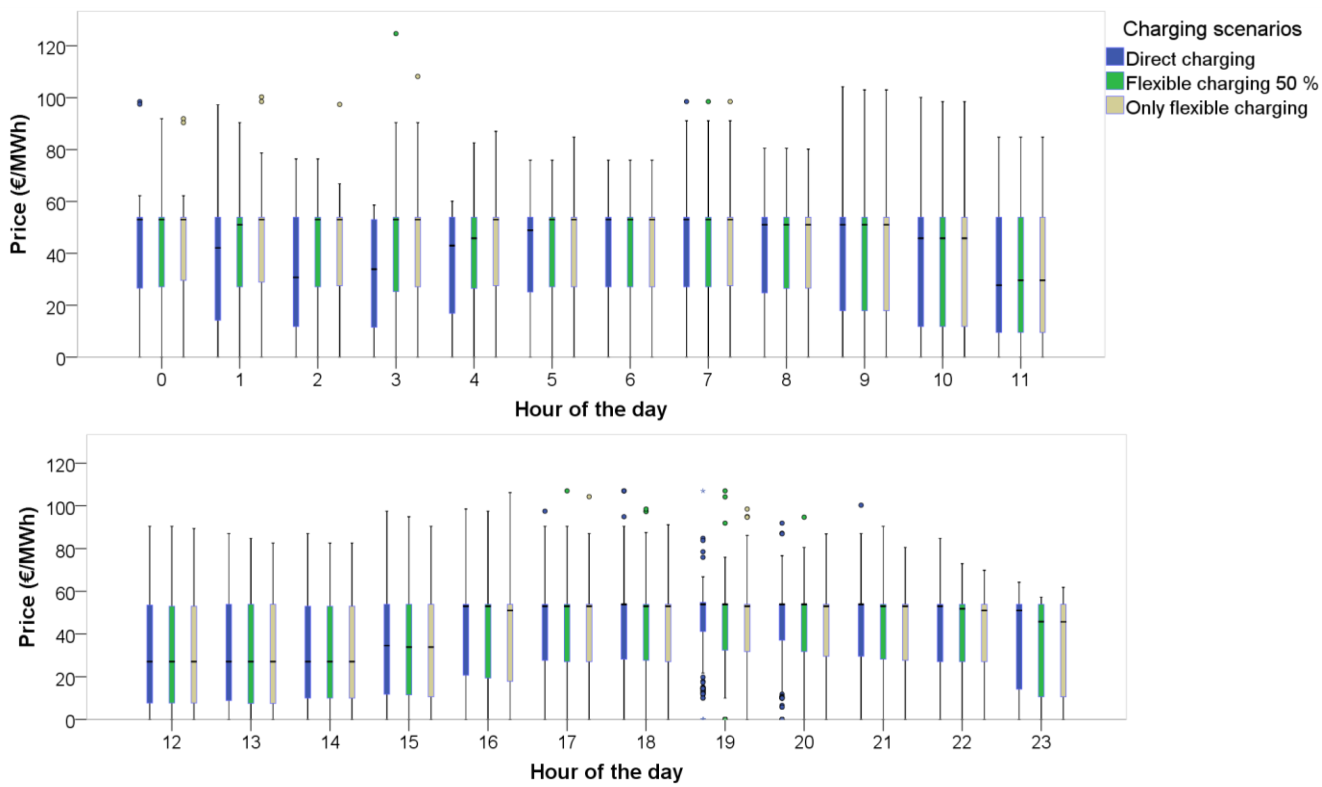

Figure 4: Box plot of simulated hourly day-ahead electricity prices for different charging scenarios

Profitability of the smart charging manager's business model

In order to assess the profitability of the smart charging manager's business model, a simplified comparison of the revenues and costs presented above is made. In all three charging scenarios and both years under consideration, the yearly contribution margin, being the difference between the generated revenues and the direct costs for purchasing electricity, is positive. However, the contribution margin is decreasing, the higher the flexibility of the smart charging manager is. The smart charging manager’s costs benefits from load shifting do not outweigh the lower revenues generated by the smart charging tariffs.

While the PowerACE model is used to estimate direct costs for purchasing electricity on the day-ahead market in future years, other costs of the smart charging manager’s business model need to be assessed alternatively. In general, the role of the smart charging manager in the electricity market is comparable to other intermediaries or aggregators, for instance, to utilities offering traditional supply contracts or to those commercializing electricity generated from renewable energy sources. Such businesses are confronted with different types of costs for setting up and maintaining the business which include, amongst others, trading fees, costs for market analyses, personal, rent, hardware (e.g. IT) and office supply. Indicative values are given, for instance, in Reeg et al. (2013) for intermediaries selling electricity generated from renewable energy sources. Based on the trading volumes in 2022 and 2030, these additional variable and fixed costs for the smart charging manager amount to yearly costs of around EURmn 0.8 and EURmn 1.7, respectively[9]. Furthermore, the capital expenditures (investments) for smart meters in households need to be financed. In order to initially incentivize households to take part in the flexible tariffs and to increase WTP, the smart charging manager could start to install the smart meters at its own expense.

Limitations

The analyses in this paper are based on several limitations. The model used for the diffusion of EV in Germany is subject to a high degree of uncertainty. In particular, it needs to be considered that the model has only been estimated using six data points including the crucial assumption that the German government’s goal in the year 2030 will be reached.

The evaluation of the WTP for the smart charging tariff presented in this paper is based on survey data which only permits deriving limited conclusions. Due to the small number of respondents, it is not representative for the German population. Other parameters must be taken into consideration as well. Notably, it should be considered that WTP for the second price level of the charging tariff considered not only depends on the fact that the EV will be charged dynamically according to the smart charging manager’s strategy of maximizing his profits, but also on the flexibility which is granted to the smart charging manager by the EV users. The survey results presented in the form of WTP for the two price levels did not take into account the influence of this parameter.

The simulation using the agent-based model PowerACE is static with respect to different aspects. The load shifting potential available to the smart charging manager is based on data from the German mobility study described above. Throughout the simulation, it is assumed that the mobility behaviour of the households is unchanged, i.e. the same specific daily trip profiles are assumed for each day. Moreover, the smart charging manager is modelled as one single agent for the whole market area. Implicitly, this means that the total trading volume from charging EV is managed by one agent. The model, therefore, does not consider any effects from competition in this industry. Furthermore, only one tariff structure is considered at a time and households cannot change their tariff over time.

The smart charging manager’s scheduling algorithm is based on a heuristic approach. The agent uses an identical price signal for all households and electric vehicles, respectively. Based on the price signal the day-ahead bids are determined. Although, this approach allows the smart charging manager effectively to profit from low prices and to avoid peaks signalled by the price forecast, it is also possible that new peaks occur depending on the volume. Thereby, the smart charging manager becomes a price maker in some situations. If detrimental, this effect is also called avalanche or herd effect (e.g. Gottwalt et al. 2011; Dallinger and Wietschel 2012). In the simulation, such situations increase with the growing diffusion of EV. To avoid such excessive effects, for instance, randomized and individual price forecasts could be used and the scheduling problem should consider the decision maker’s own potential price effect. Additionally, the agent could use a learning function to improve its bidding behaviour. By enhancing the scheduling algorithm the simulated smart charging manager agent could tap additional economic potential from load shifting activities.

Analysing simulated electricity prices in 2030 shows that prices are particularly low at noon and in the early afternoon which is mainly due to the increasing electricity generation from photovoltaics. During these hours many cars in Germany are parked at the places people work at. Hence, charging the EV at workplaces should also be an option in future analyses allowing a smart charging manager to exploit corresponding potential for load shifting activities during the whole day. The low level of prices in times of high electricity generation from photovoltaics could be an additional incentive for EV users to hand over the control of the charging process to the smart charging manager, as electricity during these times is comparably cheap and feature comparably low greenhouse gas emissions.

[9] The business model in Reeg et al. (2013) exhibits economies of scale depending on the trading volume of the intermediary. As in this paper, only one smart charging manager per market area is considered, economies of scale might be overestimated.

In the simulation a constant maximum charging power of 3.7 kW is assumed. A higher charging power (e.g. 20 kW) can have additional effects on market clearing prices and the smart charging manager's business model. In the scenario with direct charging evening peaks could increase even more, while load shifting would allow to profit additionally from periods with very low prices.

Furthermore, the simulation of the electricity market does not include any consideration of grid effects (e.g. on the distribution level) due to an increased demand for electricity to charge EV. The smart charging manager in the future could provide ancillary services, for instance to local distribution grid operators. Thereby, grid congestion might be avoided or reduced. Such aspects are not considered in this paper.

Conclusions and Outlook

In this paper, first steps are undertaken to analyse the business model of a smart charging manager. Such an entity acts as an aggregator of electricity demand from EV and manages the charging of EV considering customer needs (e.g. with respect to battery SOC) and price signals from electricity markets. In order to do so, the paper includes estimating a diffusion model for EV in Germany, assessing potential revenues for different end-user tariffs and costs for purchasing electricity in the spot market. Based on a survey with 180 respondents who have partly already been using EV and who have been asked if they could imagine to purchase an EV within the next 10 years in 2012, a binary logit model has been estimated. This allows assigning probabilities of buying EV in combination with a German representative mobility study. Knowing which households in Germany intend to purchase an EV until 2022, an EV diffusion model has been estimated (i). Furthermore, corresponding mobility patterns including usage and parking times of cars have been analysed. Different strategies of a smart charging manager using households' EV specific load shifting potentials have been analysed (ii) in order to assess potentials for business model developments (iii) and corresponding impacts on electricity demand in Germany using an agent-based simulation model for electricity wholesale markets (iv). Results indicate that the smart charging business model could be profitable in general as contribution margins are positive in the considered scenarios and years.

However, the yearly contribution margin in selected years is decreasing in the load shifting scenarios. Managing EV charging can be beneficial from a pure cost perspective as costs for purchasing electricity on the day-ahead market are lower. But the smart charging manager's cost benefits from load shifting do not outweigh the lower revenues generated by the smart charging tariffs due to the customers' lower WTP during the times they offer their load shifting potential to the smart charging manager.

In future research, several aspects are to be considered in more detail. So far, only the deterministic part of the binary logistic regression model has been considered in the simulation environment. Consequently, the ranking of households replacing their conventional cars with EV are the same during each simulation run. As the model can only explain about 30 % of the variations in the answers of the survey participants, using the variable part of the regression equation could be used for a stochastic version of the model. Furthermore, future research focusing on evaluating consumers' WTP for different variants of the load shifting dependent smart charging tariff based on a large-scale, potentially representative survey is worthwhile. With respect to the implementation of the smart charging manager in the electricity market simulation model, two extensions are suggested. First, the additional load shifting potential during the day when EV are parked at workplaces should be considered provided the availability of data. Second, the spot market scheduling algorithm of the smart charging manager is to be refined in order to reflect potential price effects and corresponding avalanche effects from its load management activities. Both aspects should allow the smart charging manager to exploit additional potentials to profit from load shifting activities in electricity spot markets.

Appendix

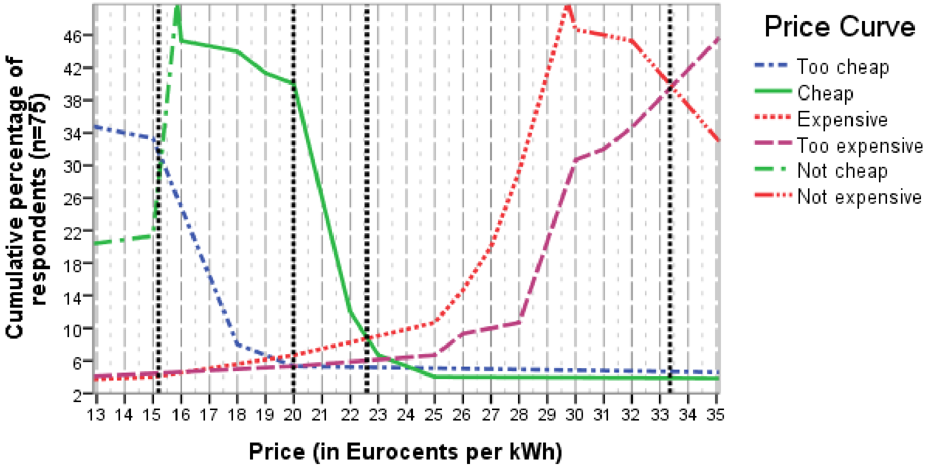

Figure 5: WTP for directly charging EV (single price level tariff)

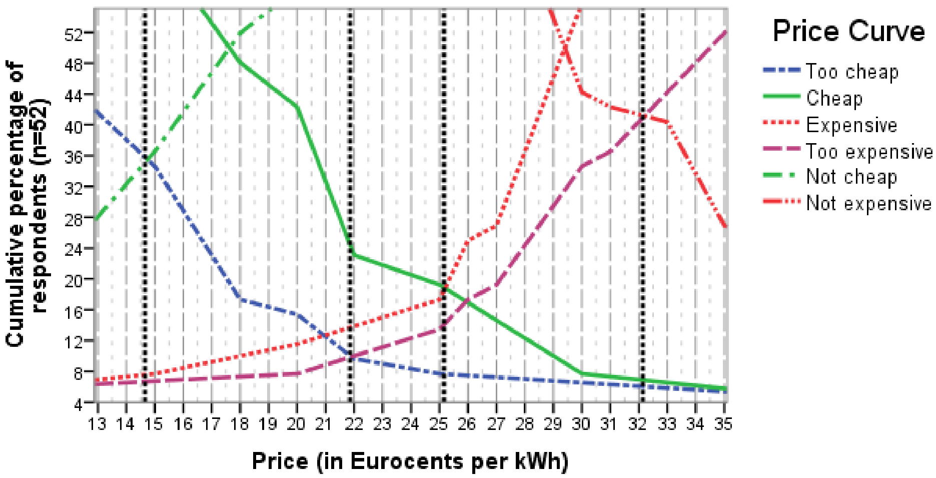

Figure 6: WTP for directly charging the EV until confidence level of the battery is reached (two price level tariff)

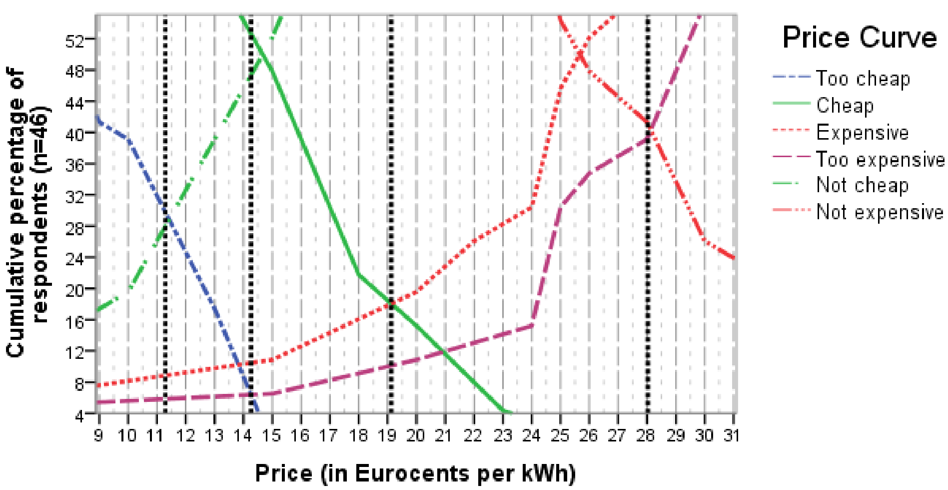

Figure 7: WTP during the time when the charging process is managed by the smart charging service provider (two price level tariff)

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