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Dutch electric vehicle drivers' preferences regarding vehicle-to-grid contracts – a context-dependent stated choice experiment considering the EV recharging speed

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Abstract

Vehicle-to-grid (V2G) could turn an electric vehicle (EV) into a potential source of flexibility, in order to deal with the variability and uncertainty in electricity supply brought about by renewable energy sources and the load increase caused by the adoption of EVs. However, only a few studies have focussed on the complexity of EV drivers' motivations towards V2G contracts. The main objective of this paper was to address this lack of empirical evidence in the V2G literature by conducting a stated choice experiment among Dutch EV drivers' to obtain their preferences regarding participating in V2G contracts with an aggregator, an intermediary party that would bundle the batteries of the EVs virtually. These preferences were measured from the perspective of an increased recharging speed of EVs. Therefore, the impact of an increased recharging speed on the potential success of V2G was also measured. In particular, the effect of an increased recharging speed on the guaranteed minimum battery level, one of the contract attributes used in both former as well as in this research, was quantified. A total of 1,332 choice observations was gathered and used to estimate an Multinomial Logit (MNL) model. The results showed that Dutch EV drivers based their decisions to choose for a particular V2G contract on a required plug-in time, a financial compensation, a number of discharging cycles and a guaranteed minimum battery level. However, the relative importance of these contract attributes depended on the recharging speed of the EVs. In fact, Dutch EV drivers valued the guaranteed minimum battery level half as important within the context of a fast recharging speed, relative to recharging speed of their current EVs. The results are compared to the few previously conducted stated choice experiment on V2G contracts, indicating that the demanded financial compensation for the significant contract attributes seems to decrease. This paper concludes with recommendations for further scientific research.

Keywords

Vehicle-to-grid, V2G, stated choice, stated preference, electric vehicle, EV, recharging speed, consumer preferences, V2G contract

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1. Introduction

There is a growing body of literature that recognises the major trends that transform today's electricity supply and transport landscape. Among these trends, two developments cause huge challenges on the electricity grid. Firstly, centralised conventional power plants are gradually replaced by small-scale decentralised renewable sources and

secondly, the electric vehicle (EV) is becoming popular and is starting to disrupt the mobility sector (Bayindir, Colak, Fulli, & Demirtas, 2016; Huda, Aziz, & Tokimatsu, 2018). The intermittent character of renewable energy sources asks for intelligent electricity storage, particularly as the adoption of EVs will increase the load. Without electricity storage, capacity problems on the grid and misalignments between electricity supply and demand will arise (Ellabban, Abu-Rub, & Blaabjerg, 2014).

In an effort to use EVs as an intelligent source of electricity storage, Kempton & Letendre (1997) introduced the concept of using car batteries as a new source of power, termed vehicle-to-grid (V2G). With this technology, an EV could become an electricity storage device when being parked and plugged in. This makes an EV a potential source of flexibility, which can be defined as the ability to deal with variability and uncertainty in electricity supply and demand (Holttinen et al., 2013). Given that EVs are not in use for driving for about 90% of the time (Hoogvliet, Litjens, & van Sark, 2017), EVs provide a high potential of electricity storage without the need for major reinforcements on the electricity grid. The use of EV batteries could therefore be an intelligent alternative to stationary storage (Tarroja, Zhang, Wifvat, Shaffer, & Samuelsen, 2016). However, as one single EV does not have enough capacity to make an impact on the grid, the role of an 'aggregator' is introduced (USEF, 2015). An aggregator gathers information and capacity from many different car batteries to aggregate them into a large source of electricity storage (Guille & Gross, 2009). The degree to which an aggregator could manage the car battery of an EV driver could be specified in a contractual relationship (Guille & Gross, 2009).

Even though V2G is a technically mature system that could offer many benefits (Geske & Schumann, 2018), a number of socio-technical dimensions are currently understudied. Firstly, only a few studies have focussed on the complexity of EV drivers' motivations towards V2G systems (Sovacool, Axsen, & Kempton, 2017). For this reason, empirical insights on specific requirements of V2G programmes are not yet widely available in V2G literature. Without these insights, future scenarios of the true potential of V2G remain unrealistic. In particular, social elements such as EV drivers, attitudes, perceptions and driving behaviour are mainly neglected in previous studies. Secondly, only four studies have empirically analysed the willingness to participate in V2G contracts (Geske & Schumann, 2018; Kubli, Loock, & Wüstenhagen, 2018; Parsons, Hidrue, Kempton, & Gardner, 2014; Zonneveld, 2019). These insights could be rather valuable for all actors in the transport and electricity supply sector. Moreover, these insights could be particularly interesting for aggregators, as they have to design their V2G contracts carefully in order to attract EV drivers that are most valuable to them (Broneske & Wozabal, 2017). In addition to these neglected socio-technical dimensions, the ongoing technological process regarding the battery development of EVs should be considered in V2G research. Parsons et al. (2014) argued that the recharging speed of an EV could have a potential influence on the overall success of V2G. In particular, the guaranteed minimum battery level, one of the contract attributes used in both former as well as in this research, could be affected by the recharging speed.

The main objective of this paper was to obtain Dutch EV drivers' preferences regarding participating in V2G contracts with aggregators. As outcomes of a stated choice experiment in the Netherlands were analysed, this research further builds on previously conducted stated choice experiments (Geske & Schumann, 2018; Kubli et al., 2018; Parsons et al., 2014; Zonneveld, 2019). The second objective was to measure the impact of the recharging speed of EVs on the potential success of V2G. In particular, the influence of an improving recharging speed on the guaranteed minimum battery level was measured.

The data collection was gathered by administering both an online and offline survey with stated choice experiment among Dutch EV drivers. In total, 148 Dutch EV drivers completed the survey. In this survey, respondents had to choose multiple times between three options, namely two hypothetical V2G contracts and one option to opt out and stick to their conventional way of charging. Subsequently, the respondents' choices were analysed with a Multinomial Logit (MNL) model in order to estimate parameters expressing the importance of the contract attributes and context variable.

This paper contributes to the empirical literature on V2G in several ways. To start with, this is the first research that investigates the relationship between a particular EV attribute with a V2G contract attribute. Specifically, the potential moderation effect of the speed of recharging on the importance of guaranteed minimum battery level is quantified. This stresses the importance of EV developments regarding the potential of V2G. Furthermore, this paper belongs to the select few studies that quantifies the relative importance of several V2G contract attributes (Geske & Schumann, 2018; Kubli et al., 2018; Parsons et al., 2014; Zonneveld, 2019). Therefore, supportive and contradicting findings compared to previous research are added to the empirical knowledge base on V2G contracts. On top of the

reproduction, the effect of two newly proposed contract attributes on the overall willingness to participate in a particular V2G contract has been measured. Finally, with respect to the collection of the data, this is the first paper that directly approached EV drivers at public fast-charging locations for their cooperation in the V2G survey.

2. Conceptual model

This section concentrates on the relevant, previously conducted stated choice experiments on V2G to obtain the most important factors that influence EV drivers in their participation in V2G contracts. These factors are conceptualized in the conceptual model in Figure 1.

2.1. Contract attributes

An aggregator should be able to control sufficient battery capacity in order to provide enough flexibility. In order to improve the predictability of storage capacity for the aggregator, an attribute for plug-in duration is part of a V2G contract. Plug-in time can be defined as average plug-in duration over a specific period. Parsons et al. (2014) and Geske & Schumann (2018) based this period on days, varying respectively from 5 to 20 and 0 to 14 hours a day. In this study, the plug-in time was restricted to 5, 10 and 15 hours per day. As plug-in times constraint the EV drivers' freedom, a negative effect on the perceived utility was expected from this contract attribute (H_3 in Figure 1).

Guaranteed minimum battery level can be defined as a minimum battery state of charge below which power aggregators will not draw power from the battery. Therefore, this attribute guarantees the EV driver will not be faced with an uncharged vehicle for unexpected trips. Parsons et al. (2014), Geske & Schumann (2018), Kubli et al. (2018) and Zonneveld (2019) all expressed this attribute in a driving-distance-equivalent charge. In this thesis, it was assumed that the lowest level of the guaranteed minimum driving range almost equalled the average daily driving range as in Geske & Schumann (2018). Assuming the aggregator does not always draw the battery down to its minimum level, this implies that EV drivers would, on average, be able to drive the average daily driving distance. Furthermore, it was chosen to express this range in percentages, as in Kubli et al. (2018), rather than in kilometres. Showing the attribute levels in kilometres could be confusing as to whether this corresponds to the theoretical or the practical distance that is left in the battery. By showing percentages, an EV driver would be able to recognise the practical distance the EV would be able to travel. Therefore, the minimum level was set to 10%, corresponding to the average daily driving range, a positive effect on the perceived utility was expected (H₄ in Figure 1).

In V2G contracts, EV drivers are to a certain extent obliged to have their EVs plugged in. This creates discomfort, which has to be compensated. Therefore, remuneration can be defined as any form of compensation for the cost of discomfort experienced by EV drivers with a V2G contract (Kubli et al., 2018). In previous stated choice experiments, remuneration was mainly based on frequent fixed payments. However, Parsons et al. (2014) proposed several other strategies to the strict cash-back-contract approach. One of them is a pay-as-you-go contract, which requires no plugin obligations. EV owners would be paid for power capacity on an hourly basis. In Lee et al. (2018), these contracts were defined as control-based contracts. It would be interesting to investigate how EV drivers would value another remuneration approach. Next to the fixed periodically payments based on the plug-in time, a variable extra remuneration could be provided for every extra hour an EV is plugged in on top of the pre-specified plug-in time. This would both result in a backup capacity for the aggregators secured by the plug-in time, as well as an incentive for EV drivers to plug-in their EVs more often. Therefore, in this research, remuneration was based on these two components. The first component included a fixed monthly payment, as being used in the previous studies. On top of that, a variable extra remuneration component was added as a contract attribute for which a separate parameter was estimated. Both remuneration components made up the hybrid remuneration structure, which was defined as a fixed as well as a variable monthly payment. This variable monthly payment was based on an hourly rate, multiplied by the number of hours an EV was plugged in per month above the required plug-in time. The attribute levels of the remuneration in this research have been chosen to be less than those in the research of Zonneveld (2019), as extra variable remuneration could be obtained by being plugged in for more hours than the EV driver is obliged to. Therefore, the levels of fixed remuneration were set to $\notin 20, \notin 60$ and $\notin 100$ per month and the levels for variable extra remuneration to $\notin 0.00, \notin 0.15$ and €0.30 per extra hour outside of the plug-in time obligations. An average extra plug-in time of five hours a day would thus correspond to respectively €0, €23 and €45 variable extra remuneration per month. Both fixed and variable extra remuneration were expected to have a positive effect on the perceived utility (H_1 and H_2 in Figure 1).

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Even though the true impact of V2G on battery degradation has not yet determined (Wang, Coignard, Zeng, Zhang, & Saxena, 2016), EV drivers could base their decisions to choose for a particular V2G contract on this aspect. Kubli et al. (2018) introduced a flexibility attribute, implying the level of flexibility a prosumer could create. Next to the guaranteed minimum driving range, this flexibility attribute also included a unit for battery degradation. This degradation was defined in terms of number of discharging cycles per day. Therefore, the flexibility attribute indicated the number of times an aggregator used the battery discharging in a day, varying from 1 to unlimited numbers a day. This attribute level range is, in fact, infinite. Zonneveld (2019) narrowed this range down to three attribute levels of 1, 4 and 7 discharging cycles per session, implying a barely, moderate or large effect on the batteries' longevity. In this paper, it was assumed that one V2G session corresponded to one day. As not many new insights were obtained in literature regarding battery degradation, the same attribute level range as in Zonneveld (2019) were used in this research. Furthermore, it was expected that a higher number of discharger cycles resulted in a lower perceived utility. Therefore, a negative effect was expected (H₆ in Figure 1).

The contract duration was included as a contract attribute in the studies of Kubli et al. (2018) and Zonneveld (2019). It can be defined as the length of the contract between the aggregator and EV owner. Kubli et al. (2018) varied the attribute levels from 0 month – implying that a contract could be cancelled anytime – to 48 months. Zonneveld (2019) based these levels on the contract duration of phone subscriptions, resulting in contract durations of one month, one year or two years. As it might be the case that an aggregator will pay for the V2G charger, a contract of one month is rather short. Therefore, the one-month contract from Zonneveld (2019) was replaced by a six-month contract in this research. This results in attribute levels of 6, 12 and 24 months. It was expected that EV drivers preferred a short contract over a long contract. Therefore, a negative effect of contract duration on the perceived utility was expected (H₅ in Figure 1).

2.2. Recharging speed

Recharging speed has always been an important attribute for the adoption of EVs. The same barriers regarding the complexity of EV drivers' preferences towards EV attributes now apply for V2G attributes. Various studies have been performed on preferences and trade-offs of EV attributes. In fact, Hackbarth & Madlener (2016) and Hidrue, Parsons, Kempton, & Gardner (2011) both conducted a stated choice experiment to calculate the willingness-to-pay for EV attributes. Parsons et al. (2014) built on the research of Hidrue et al. (2011) by adding V2G attributes. However, as the preference for EV attributes were estimated in a separate experiment and were kept constant in the experiment with V2G attributes, no information about trade-offs between EV attributes and V2G attributes could be observed. In particular, Parsons et al. (2014) expressed the need for a carefully examined trade-off between the EV attribute of recharging time and the V2G attribute of guaranteed minimum driving range. The relative importance of guaranteed minimum driving range might be lower when it takes less time to recharge the EV. This was also expressed by a survey distributed in 2012, which found that respondents had a larger concern about the battery range than the costs of an EV (Egbue & Long, 2012).

Currently, many research and development departments are trying to develop batteries with a faster recharging speed (Kottasova, 2018), some arguing to be able to fully recharge an EV within five minutes in the near future (StoreDot, n.d.). As the development of batteries is an ongoing process, the speed of recharging could be of influence on the willingness to participate in V2G programmes. In particular, as proposed by Parsons et al. (2014), it would be interesting to measure the importance of the guaranteed minimum battery level in a hypothetical future scenario in which the speed of recharging of EVs approximates the recharging speed proposed by (Kottasova, 2018; StoreDot, n.d.). Therefore, recharging speed was added as a context variable to the conceptual model. This variable consisted of two levels. In the first level, the respondents were made to imagine that the EV recharges according to current recharging speeds. In the second level, a hypothetical future scenario was created, in which the respondents were made to imagine that the EV was able to fully recharge within five minutes at every charging point. Even though this would probably never be the case in real life, the effect of an increasing recharging speed (or decreasing recharging time) on the sensitivity of guaranteed minimum battery level could be measured. In order to increase the variance, it was chosen to randomly assign one context per choice set. The respondents' annoyance regarding the varying contexts within the survey remained limited, as only two contexts existed. Therefore, one respondent received choice sets in the first as well as in the second context. It was expected that EV drivers were less sensitive to guaranteed minimum battery level if the EV recharging speed was fast (H₇ in Figure 1).



Figure 1: Conceptual model

3. Survey and stated choice experiment design

In this section, the design of the survey and the stated choice experiment is described, as well as the process of distributing the survey.

3.1. Survey design

After conducting a small pilot (N=31) in order to correct for errors and unexpected bias, to test the comprehensibility of the survey and to obtain prior parameters for the efficient design of the final survey, both an online and offline survey with stated choice experiment among Dutch EV drivers was conducted from 28 May to 4 July 2019. In total, 148 Dutch EV drivers completed the final survey. Socio-demographic characteristics of the sample are displayed in Appendix A. The final survey was composed of an introduction and informed consent page, an explanation section with video clip, nine choice sets and additional questions on socio-demographics and other EV driver characteristics.

In the introduction section, the topic as well as the experiment was explained. Two simple questions that were related to the topic were asked. First, as a respondent would only qualify if he or she drove a full EV, a multiple choice question asked whether the respondent had a full EV, a plug-in hybrid EV or something else. In addition to this question, the respondent was asked if he had ever heard of V2G. In 2013, only 1% of the German vehicle users indicated that they had heard of V2G and that they knew something about it (Geske & Schumann, 2018). As part of the introduction, an informed consent page was added. Subsequently, information about V2G and the experiment was given in the explanation section. As respondents are generally not willing to read long texts of information, a short video clip was created in PowToon and uploaded on YouTube. The clip was embedded in the online pilot survey and could be viewed directly. It explained the concept of V2G and what was expected from the respondents in the experiment. In the video the contract attributes were explained. For convenience, these were written out in the survey as well. Finally, in the experimental stage of the survey, the respondents were asked to choose between three contracts nine times in a row. Two out of three alternatives consisted of a V2G contract - V2G Contracts A and B. The third option was a 'no V2G at all' alternative. In order to be able to still gather information on trade-offs between options A and B, the respondents were asked two questions for every choice set. In the first question, the respondents had a choice between all three alternatives. In the second question, though, the respondents had to choose between one of the two contracts. The 'no V2G contract' alternative was not an option in the second question. The respondents were made to answer each question, which resulted in less uncompleted surveys. An example choice set from the survey is shown in Appendix B.

3.2. Stated choice experiment

In a stated choice experiment, respondents are asked to make a choice out of hypothetical alternatives, which makes it a data collection method based on an experimental design constructed by the researcher. The attributes defined in the conceptual model in **Figure 1** were included in the choice sets of the stated choice experiment. All attributes with corresponding attribute levels are shown in **Table 1**.

Table 1: Attributes and attribute levels used in the stated choice experiment

Attributes	Attribute levels
Fixed remuneration [€ / month]	€ 20.00 per month
	€ 60.00 per month
	€ 100.00 per month
Variable extra remuneration [€ / extra hour]	No variable extra remuneration
	€ 0.15 per extra hour plugged-in outside of contract
	€ 0.30 per extra hour plugged-in outside of contract
Guaranteed minimum battery level [%]	10%
	30%
	50%
Plug-in time [hours / day]	5 hours per day
	10 hours per day
	15 hours per day
Discharging cycles [# / day]	1 time per day
	4 times per day
	7 times per day
Contract duration [months]	6 months
	12 months
	24 months

3.3. Distribution of the final survey

The final survey was distributed online as well as offline. The online survey was distributed by use of an anonymous link. For the offline distribution, another sampling approach was executed. Several public charging points were visited. In order to be able to sample as efficiently as possible, the charging points had to meet four requirements. First, the locations should include fast chargers. Second, they should show characteristics of a 'charge-and-ride' location, which maximizes the probability of EV drivers waiting in their vehicles during the charging process. Third, they should be easily accessible. Fourth, they should have a large capacity and therefore be busy. Three locations had been chosen: one Fastned location (Den Ruygen Hoek-West) and two Tesla Superchargers (Schiphol and Zwolle).

4. Model specification

The discrete choice data obtained from the stated choice experiment could be analysed with a Random Utility Maximization (RUM) model. In particular, an MNL model was used to estimate the parameters.

4.1. Random Utility Maximization

First, RUM theory assumes that the decision maker sums up the multiplication of all attribute levels with the corresponding weights (or importance) of each alternative to obtain the utility per alternative. Second, the decision maker compares the utility levels of the alternatives. RUM theory assumes that only utility levels are compared to each other. Third, the decision maker chooses the alternative that has the highest utility. In the context of this research, the choice sets consisted of three alternatives (V2G Contract A, V2G Contract B and 'no V2G contract') and every alternative was described by seven attributes that consisted of three attribute levels each (defined in Table 4 in Chapter 2).

The total utility consists of both a systematic utility and an error term, from the researcher's perspective. The systematic utility contains factors that can be observed and measured by the researcher. The error term is based on all other factors that have an influence on the total utility, but cannot be observed and measured by the researcher. This could, for instance, be the case if an important attribute is missing in the choice set. Therefore, based on the RUM theory, the total utility of alternative i chosen by decision maker n is expressed in equation (1):

 $U_{in} = V_{in} + \varepsilon_{in} \tag{1}$

In equation (1), U_{in} denotes the total utility of alternative *i*, V_{in} denotes the systematic utility and ε_{in} denotes the unobserved error. The systematic utility is expressed in equation (2):

$$V_{in} = \sum_{m} \beta_m \times X_m \tag{2}$$

In equation (2), V_{in} denotes the systematic utility of alternative *i* and β_m denotes the weight parameter associated with attribute X_m , which represents the importance of the attribute. The βs correspond to the parameters that are to be estimated with a discrete choice model, which is described in section 3.2.2. Furthermore, alternative *i* is chosen over alternative *j* if U_{in} has the maximum value. This is expressed in equation (3):

$$\sum_{m} \beta_m \times X_{im} + \varepsilon_i > \sum_{m} \beta_m \times X_{jm} + \varepsilon_j, \forall j \neq i$$
(3)

4.2. MNL model

The MNL model is an easy-to-use estimation model based on the RUM theory and proposed by Daniel McFadden. This closed form estimation model is one of the most widely used RUM models and is based on the assumption that the error term is independently and identically distributed across all alternatives with a type I extreme-value distribution and are thus drawn independently from distribution with the same variance. The systematic utility V_{in} is based on attributes with linear parameters. Hence, the linear-additive utility maximization. The choice probability P_i of alternative *i* chosen by the decision maker *n* could be found using the formula in equation (4):

$$P_i = \frac{\exp(V_{in})}{\sum_{j=1\dots J} \exp(V_{jn})} \tag{4}$$

5. Results

This section reports the results of the study. First, the influence of recharging speed on the EV drivers' choice distributions is discussed. Second, the estimations results of the MNL models are presented and interpreted.

5.1. Importance of recharging speed

Every choice set contained a particular context. In the first context, the 'status quo', the respondents had to assume a normal EV recharging speed. In the second context, the hypothetical future scenario, the respondents had to assume that their EV could fully recharge within five minutes. Interestingly, as can be deducted from **Figure 2**, the 'no V2G contract' option is less preferred within the context of fast recharging speed. This is so for every choice set. More specifically, the percentage range of the respondents choosing for the 'no V2G contract' option decreased from 48-19% in the context of normal recharging speed to 38-12% with a fast recharging speed, which is on average a reduction from 34% to 24%. In other words, more than one-third of the respondents at the moment does not prefer a V2G contract over conventional charging, while only less than a quarter would not prefer this if the recharging speed was faster. This could indicate that a faster recharging speed of an EV has indeed a positive effect on the willingness to participate in V2G contracts.

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Figure 2: Share of respondents that have chosen the 'no V2G contract' option for every choice set

5.2. Estimation results

As can be seen from Table 2, four MNL models have been estimated. In the first MNL model, only linear components were included. Additionally, MNL models A, B and C were extended with a combination of quadratic components for plug-in time and guaranteed minimum battery level, in order to test these contract attributes for non-linearity.

	Linear M	NL model	MNL mod	el A	MNL mod	lel B	MNL mod	el C
Parameter name	Value	p-value	Value	p-value	Value	p-value	Value	p-value
β _{CON}	-0.0464	0.29*	-0.00782	0.11*	-0.00603	0.18*	-0.00621	0.16*
β _{DIS}	-0.0485	0.00	-0.0339	0.04	-0.0406	0.00	-0.0449	0.00
β_{EREM}	-0.243	0.34*	-0.306	0.34*	-0.132	0.61*	-0.156	0.54*
β _{guar}	0.0411	0.00	0.0212	0.37*	0.0429	0.00	0.0439	0.00
β _{guarqua}	_	_	0.000375	0.35*	_	_	_	_
β _{PLUG}	-0.143	0.00	0.114	0.13*	0.0761	0.22*	_	_
β _{PLUGQUA}	_	_	-0.0132	0.00	-0.0111	0.00	-0.00753	0.00
β _{REM}	0.00697	0.00	0.00791	0.00	0.00704	0.00	0.00710	0.00
β _{GUARSPEED}	-0.0216	0.00	-0.0218	0.00	-0.0218	0.00	-0.0218	0.00
Number of estimated parameters	7		9		8		7	
Number of observations	1,332		1,332		1,332		1,332	
Null log-likelihood	-923.272		-923.272		-923.272		-923.272	
Final log-likelihood	-822.116		-815.188		-815.608		-816.336	
Rho-squared	0.110		0.117		0.117		0.116	

Table 2: MNL estimation results. * corresponds to an insignificant parameter estimate

In MNL model A, a quadratic component for both plug-in time as well as for guaranteed minimum battery level were included. However, the estimation of this model resulted in many insignificant parameters. In MNL model B, the quadratic component of guaranteed minimum battery level was excluded. As a significant parameter of the quadratic component of plug-in time was estimated, while the parameter estimate of the linear component of plug-in time was insignificant, MNL model C was estimated, only including a quadratic component for plug-in time. The quadratic component of plug-in time remained significant, implying that the linear effect of this component was explained away by the quadratic component. This demonstrates a quadratic effect of the parameter estimate of plug-in time on the total utility. As can be seen from the two final log-likelihoods from the linear MNL model and MNL model C (-822.1 and -816.3), it can be concluded that MNL model C fitted the data best. Therefore, the estimated parameters from MNL model C were used for the analysis of the results.

5.2.1. Relative importance

Five out of seven estimated parameters were significant at 1% level (Table 2). The relative importance of the contract attributes could be obtained by calculating the utility contributions, which could be calculated by multiplying the weights of the parameter estimates with the total attribute level range. For both contexts, discharging cycles was the least important contract attribute, followed by the fixed remuneration. When a context of normal recharging speed was assumed by the respondents, the guaranteed minimum battery level was the most important contract attribute.

Furthermore, plug-in time was the second most important factor for EV drivers' decision making regarding V2G contracts. When a context of fast recharging speed was assumed by the respondents, an interesting observation could be made. The weight of the interaction effect of recharging speed on the guaranteed minimum battery level was - 0.0218 (Table 2). Consequently, the calculated weight of the guaranteed minimum battery level was moderated by the context variable from 0.0429 to 0.0211 (0.0429 minus 0.0218). Therefore, the guaranteed minimum battery level became half as important in the context of fast recharging speed, relative to the normal recharging speed. Consequently, plug-in time became the most important attribute in the context of fast recharging speed.

5.2.2. Implicit prices

To start with, the weight of the parameter estimate of fixed remuneration had a positive effect on the total utility. This is fully in line with previous studies and expectations. The effect is linear, implying that the marginal utility increase – or in other words, the direction coefficient of the utility function of fixed remuneration – is constant. In order to compare the significant parameter estimates of plug-in time, guaranteed minimum battery level and discharging cycles in monetary terms, implicit prices were calculated. The implicit prices were calculated by dividing the parameter estimates of the parameter estimate of the fixed remuneration. Consequently, the monthly willingness-to-pay (positive sign) or monthly demanded financial compensation (negative sign) for a one-unit increase of a particular contract attribute was calculated.

It was observed that respondents experienced a large inconvenience for plug-in time. Therefore, this attribute had a negative effect on the perceived utility. The utility function of this attribute shows a quadratic effect, implying a utility contribution with an increasing rate. This effect is graphically shown in **Figure 3**. This quadratic component is in line with the findings in Parsons et al. (2014). Here, increasing the plug-in time from 5 to 10 hours a day, would have to be financially compensated with €79.54 per month. Further increasing the required plug-in hours from 10 to 15 hours, would correspond to a demanded financial compensation of €132.57. This implies a required per-hour incremental financial compensation of €15.19 (5-10h) and €26.51 (10-15h) per month.



Figure 3: Quadratic utility contribution of the plug-in time attribute. The grey dashed line is an extrapolation of the results.

The contract attribute of guaranteed minimum battery level had a positive effect on the total utility. Therefore, increasing the level of this attribute resulted in a higher probability that a particular contract will be preferred. When considering the context of normal recharging speed, this attribute was valued as most important to the respondents. Interestingly, when assuming a fast recharging speed, the weight of this parameter estimate became half as important. It is calculated that a 1%-increase in guaranteed minimum battery level was worth ϵ 6.04 per month to the respondents in a battery level range of 10-50%. This reduced to ϵ 2.97 per month in the context of fast recharging speed. As the average range of a full EV battery in this study's sample equalled approximately 360 km, this range corresponded to 36-180km. Moreover, this means that an increase in one kilometre is valued at ϵ 1.68 per month. Interestingly, this valuation reduces to ϵ 0.83 in the context of fast recharging speed. The lower the specified guaranteed minimum battery level in a V2G contract, the higher the value for an aggregator is. Therefore, the development of battery recharging speed could influence the social acceptance of V2G contracts in a positive way.

As was expected, the attribute of discharging cycles had a negative effect on the perceived utility. Even though an effect of discharging cycles existed, it was the least important factor of the significant parameters. One extra discharging cycle would have to be financially compensated with $\in 6.32$ per month in order to be accepted by the respondents.

5.2.3. Reflection on conceptual model

When the weights of the estimated parameters that were statistically significant were substituted in the utility functions, the following systematic utility function for a V2G contract was found:

 $V_{V2G \ Contract} = 0.00710 \cdot REM - 0.00753 \cdot PLUG^2 + (0.0429 - 0.0218 \cdot SPEED) \cdot GUAR - 0.0449 \cdot DIS$

The weight of the guaranteed minimum battery level depended on the context variable. Therefore, by substituting the two variables for *SPEED* (0 or 1), the following two systematic utility functions for both normal recharging speed as well as for fast recharging speed arose:

V_{V2G} Contract, Normal Recharging Speed	=	$0.00710 \bullet REM - 0.00753 \bullet PLUG^2 + (0.0429) \bullet GUAR - 0.0449 \bullet DIS$
V_{V2G} Contract, Fast Recharging Speed	=	$0.00710 \bullet REM - 0.00753 \bullet PLUG^2 + (0.0429 - 0.0218) \bullet GUAR - 0.0449 \bullet DIS$

As shown by the two utility functions, the weight for the guaranteed minimum battery level depends on the recharging speed. Note that the terms for variable extra remuneration as well as for contract duration were excluded from the utility function, as their parameter estimates were statistically insignificant. Fixed remuneration, plug-in time, guaranteed minimum battery level, discharging cycles and the interaction effect of recharging speed were correctly hypothesized.

6. Conclusions

To the knowledge of the researcher, this is the first research that has empirically analysed the effect of an improving recharging speed on V2G contracts. In fact, a significant moderation effect of the EV recharging speed on the guaranteed minimum battery level was found. The respondents in this sample valued the guaranteed minimum battery level was found. The respondents in this sample valued the guaranteed minimum battery level was found. The respondents in this sample valued the guaranteed minimum battery level – relative to the 'status quo', or normal recharging speed – half as important if the EV would be able to fully recharge within five minutes. Even though this hypothetical recharging speed is not yet feasible and perhaps a little overdone, this confirms that interesting trade-offs between EV and V2G attributes provide valuable insights. Moreover, it has been determined that, on average, 34% of the respondents did not prefer a V2G contract over conventional charging in the 'status quo' scenario, against only 24% in a fast recharging speed context. Therefore, the development of the battery recharging speed could have a beneficial influence on the adoption of V2G contracts.

Furthermore, four out of seven contract attributes had a significant effect on the total perceived utility for a V2G contract and were correctly hypothesized, according to the parameter estimations. Interestingly, the order of relative importance of the significant contract attributes differed per context. Within the context of normal recharging speed, guaranteed minimum battery range had the largest utility contribution. However, due to the interaction effect of recharging speed on the guaranteed minimum battery level, plug-in time became the most important contract attribute within the context of fast recharging speed. In particular, due to the quadratic function, plug-in time became the constraining contract attribute with levels above 10 hours per day.

In order to increase the tangibility of the results, implicit prices for every significant contract attribute were calculated. Compared to previous studies, these implicit prices seemed to decrease. This could imply that EV drivers slowly start to recognize the need for such flexibility solutions. In fact, a one-kilometre increase in guaranteed minimum battery level is worth \pounds 1.68 per month assuming the current speed of recharging. This reduces to \pounds 0.83 per month when the speed of recharging reduces to five minutes. Furthermore, one extra discharging cycle per V2G session should be compensated with \pounds 6.32 per month. Finally, a one-hour increase in plug-in time in the range of 5 to 10 hours per day should be financially compensated with \pounds 15.91 per month. Due to the quadratic utility function for plug-in time, this required financial compensation increases to \pounds 26.51 per month for every one-hour increase in the range of 10 to 15 hours.

7. Discussion

This final section compares the obtained findings with previous findings in the V2G literature. Furthermore, scientific recommendations for further research are provided.

7.1. Comparison with previous stated choice experiments on V2G

The weight of the fixed remuneration is in line with the findings of Geske & Schumann (2018), as remuneration is apparently not the most important contract attribute. This is in contrast with the estimation results of Kubli et al. (2018) and Parsons et al. (2014). An explanation for this could lie in the relatively high income levels of the sample in this study. High income individuals might be less sensitive to financial incentives.

This study found relatively low implicit prices for plug-in times compared to the study in Parsons et al. (2014). These were estimated at \pounds 247.96 (5-10h) and \pounds 534.61 (10-15h) per year, respectively \pounds 20.66 and \pounds 44.55 per month. As an average vehicle is parked for around 95% of the day, Parsons et al. (2014) argued that these incremental costs were surprisingly high. Apparently, respondents did not treat plug-in time as a potential of increasing the productivity of their parked vehicles. Instead, they only focussed on the inconveniences a high plug-in time would cause. In this study, the respondents did seem to see more potential for their parked vehicles, as they demanded less financial compensation for an increase in plug-in time. This could partly be explained by the fact that the survey in Parsons et al. (2014) was distributed as early as 2009, even before EVs were widely adopted. Another explanation could be that the sample in this study only consisted of EV drivers, while the sample in Parsons et al. (2014) also included conventional vehicle drivers in their sample. The reduction in demanded financial compensation for plug-in time has a beneficial as well as a disadvantageous implication for the aggregator. On the one side, the potential inconveniences respondents see with plug-in times seem to be reduced, allowing an aggregator to increase its predictability of available battery capacity for ancillary services. On the other side, increasing the number of required plug-in hours to above 10 hours per day would result in a relatively high demanded financial compensation.

This study also found relatively low implicit prices for the guaranteed minimum battery level. The average perkilometre incremental willingness-to-pay from a range of 10-50km was calculated at \notin 5.13 per month by Geske & Schumann (2018). Parsons et al. (2014) found the utility contributions to behave as a quadratic function. An increase in the range of 40-120km would be worth \notin 4.01 per month for every one-kilometre increase. Furthermore, these valuations reduced to \notin 3.19 and as little as \notin 0.46 in respectively the ranges of 120-200km and 200-280km.

An explanation for the relatively low importance of the number of discharging cycles could be that a large part of this sample (64.9%) leases an EV. They might be less concerned about battery degradation, as they do not own the vehicles themselves. However, this does introduce an implication for the leasing companies, as they own the vehicles and could be more concerned about potential damage to the batteries.

Finally, regarding the offline data collection method, the offline sampling approach turned out to be an excellent sampling strategy to increase the number of respondents. As many EV drivers wait in their EVs for at least twenty minutes while charging, practically every single one of the approached EV drivers reacted friendly on approach, were willing to fill in the survey and were genuinely interested in the research. As offline distribution might have increased the sample variance in terms of socio-demographic factors, the validity of the research increased as well. For further research on V2G contracts, an offline sampling approach at public fast chargers would definitely be recommended.

7.2. Recommendations for further scientific research

Two interesting contract attributes that have not been measured yet can be proposed. First, free parking as an alternative remuneration method could be explored. Instead of a financial compensation, citizens would be able to take advantage of free parking initiatives in exchange for V2G services. It would be interesting to quantify how EV drivers would value such remuneration schemes compared to rather straightforward remuneration schemes from previous studies. Secondly, Geske & Schumann (2018) measured the importance of an on-board computer in which EV drivers could specify their trips. In this way, they could plan trips in advance. This would increase the reliability of plug-in times for the aggregator. In Geske & Schumann (2018), the relative importance of an on-board computer was higher than plug-in time as well as remuneration. Even though this parameter would increase the complexity of the survey for the respondents, a stated choice experiment could be designed that would measure this contract attribute in particular.

Furthermore, this research only included one context variable. Two additional context variables that would also be interesting to research are the type of parking and the ownership of a second car. First, the difference in short-term and long-term parking could be investigated. This study did not make an explicit distinction between these two types of parking. It would be interesting to measure V2G's potential from the perspective of long-term parking relative to short-term parking. It would, for instance, be interesting to find out whether V2G contracts would be valued differently than was the case in this research if the EV driver was not using the EV for an extended period, during for instance a holiday by plane. If so, exploiters of parking spaces at airports could investigate new business models. Secondly, several respondents mentioned having a second car and argued to be in favour of V2G programmes due to the ownership of this second car. The potential positive effect on the willingness to participate in V2G contract because of being able to use a second car could also be quantified by using a context variable. In fact, having a second vehicle would take away much of the discomfort experienced by long plug-in time requirements or low battery levels. This would give the aggregator an indication on whether to target more heavily on EV drivers that own more than one vehicle or not.

Noted must be, however, that if the number of the to be estimated parameters increases by enlarging the number of either contract attributes or context variables, more respondents will be needed to be able to estimate statistically significant parameters.



Appendix A: Socio-demographic characteristics

Figure 4: Socio-demographic characteristics of the sample population (n=148). Note that the offline respondents did not fill in their income. Therefore, this income distribution is only based on the 106 online respondents.

Appendix B: Survey

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Vergelijk onderstaande V2G contracten en beantwoord de twee corresponderende vragen.

Context	Uw elektrische auto kan overal <u>volledig opladen in 5 minuten</u> – ook aan uw thuislader!					
Contract Attributen	V2G Contract A	V2G Contract B				
Financiële vergoeding	€20 per maand + €0.30 per extra uur bovenop minimale inplugtijd	€100 per maand + €0.00 per extra uur bovenop minimale inplugtijd				
Minimale inplugtijd	5 uur per dag	10 uur per dag	Geen V2G Contract			
Gegarandeerd batterij level	10 %	30 %				
Ontlaad frequentie	$7~{ m x}$ per dag	1 X per dag				
Contract lengte	24 maanden	6 maanden				

Als ik tussen alle drie de opties zou kunnen kiezen, gaat mijn voorkeur uit naar:

- O V2G Contract A
- O V2G Contract B
- O Geen V2G Contract

Als 'Geen V2G Contract' geen optie is, gaat mijn voorkeur uit naar:

- O V2G Contract A
- O V2G Contract B

Figure 5: Example choice set from the final survey

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