Measuring Consumer Willingness to Enroll in Battery Electric Vehicle Smart Charging Programs

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Word Count: 4502 words + 6 table(s) × 250 = 6002 words

Submission Date: July 30, 2024

ABSTRACT

As Battery Electric Vehicles (BEVs) gain popularity, managing their charging becomes crucial for balancing electricity supply and demand on the grid. Smart charging programs can help utilities manage this demand and integrate more renewable energy by controlling when and how BEVs are charged. However, these programs require participation from BEV owners, who may be hesitant to freely provide such control. This study uses a discrete choice experiment (also called conjoint analysis) to measure BEV owners' willingness to participate in smart charging programs under various incentives and features. We examine two types of smart charging: Supplier-Managed Charging (SMC), which controls charging times, and Vehicle-to-Grid (V2G), allowing BEVs to return power to the grid. In an online survey conducted via Facebook and Instagram ads, we collected 858 valid responses, with 815 responses for SMC program choices and 414 for V2G program choices. We used mixed logit (MXL) models to quantify respondents' willingness to participate in these programs. The findings indicate a general reluctance to participate in both programs without some form of incentive, with respondents being most sensitive to regular (monthly) monetary incentives. For SMC, there is also concern about ensuring sufficient battery charge levels in the mornings. Simulations were conducted to predict enrollment rates based on different program features. Additional data will be collected to refine the models in the coming months.

Keywords: Smart Charging, Grid Management, Consumer Preferences, Discrete Choice Experiment (DCE), Logit Models, Battery Electric Vehicle (BEV), Vehicle-to-Grid (V2G).

INTRODUCTION

Battery electric vehicles (BEVs) are a cornerstone in plans to decarbonize the U.S. energy system (*1*). As a result, they are also expected to be the largest source of electricity demand in the coming decades, but the timing of that charging could be detrimental to sustainability and infrastructure longevity if left unmanaged (*2*). Due to patterns in BEV owner behavior, BEV charging often coincides with peak electricity demand on regional electric grids, which can lead to increased strain on the grid and increased greenhouse gas (GHG) emissions (*3*). A solution is to align BEV charging with off-peak electricity demand periods, which can alleviate these problems and help reduce the curtailment of renewable electricity sources such as wind and solar (*2*).

One strategy to achieve this outcome is "smart charging," an approach where BEV owners provide utilities control over charging to smooth out the electricity demand and re-align it with off-peak periods. There are two major approaches for smart charging: Supplier-Managed Charging (SMC), which monitors and controls the timing of the charging, and Vehicle-to-Grid (V2G), which enables BEVs to send power back to the grid, providing grid operators even more flexibility in load balancing. Both SMC and V2G have been found to be economically beneficial to the grid and facilitate greater use of renewable energy (*2, 4*).

The promise of smart charging rests on the willingness of BEV owners to give utilities control over their charging. Many are unwilling to do so freely due to privacy concerns, the potential for reduced operational capabilities (e.g. waking up with insufficient charge), and inadequate compensation (*5, 6*). This research aims to quantify how different smart charging program incentives and control settings can align with BEV owner charging preferences. We address two research questions:

- How do changes in individual smart charging program features influence the willingness of BEV owners to opt in to SMC and V2G programs?
- Under what conditions will BEV owners be more willing to opt-in to SMC and V2G programs?

We address these questions using a survey-based discrete choice experiment (also called "conjoint analysis") to quantify user preferences for different smart charging program features.

BACKGROUND

BEVs are a promising alternative to gasoline-powered conventional vehicles (CVs). They can significantly reduce vehicle life cycle GHG and criteria pollutant emissions (*7*), and thus they can support the incorporation of renewable or low-carbon electricity generation into the grid (*8*). These benefits are largely dependent on the emissions intensity of the electricity sources used for charging these vehicles (*9*) and the timing of vehicle charging. Studies have shown that peak BEV charging typically happens when renewable or low-carbon resources are limited (*10*). Therefore, without effective charging management, the GHG emissions reduction potential of BEVs may be limited (*2*).

A complementary approach is to leverage the BEVs themselves to offer the required flexibility for balancing the fluctuating electricity generation from renewable sources (*11*). This strategy, referred to generally as "smart" or "grid-communicative" charging, can be executed in multiple ways. In this study, we focus on two common strategies: SMC and V2G. SMC involves BEV owners sharing information about their vehicle's charging needs with utilities, allowing them to manage the charging schedule. This allows utilities to charge when it is more convenient, such as during off-peak periods or during times of surplus low-carbon electricity, while ensuring the battery reaches a desired charge level by a predefined time (*12*). V2G offers even greater potential benefits by enabling two-way charging, where utilities can also discharge electricity from BEVs back to the grid. These V2G scenarios provide enhanced flexibility and could lead to more significant emission reductions compared to SMC alone (*13*). However, V2G also increases the frequency of battery cycling, which could potentially accelerate battery degradation (*14*). In order to hedge the anxiety of battery degradation, monetary returns and guaranteed battery thresholds are important incentives for increasing BEV owners' willingness to participate in these programs (*15*).

The potential benefits of SMC and V2G programs are well-documented under ideal conditions of full BEV owner adoption (*2, 16*). Therefore, the success of these programs hinges on BEV owners' willingness to participate. For example, in a real-world experiment of a SMC program, a study by Bailey et al. (*17*) found that once financial incentives were removed, BEV owners stopped participating and returned to their original charging habits. It is therefore crucial to understand the conditions under which BEV owners are more likely to participate in smart charging programs. As BEV adoption and renewable energy deployment continue to grow, this information will be vital for utilities to make investment and operational decisions.

One commonly used approach to assess preferences for a variety of smart charging features is discrete choice experiments. A recent study by Wong et al. (*18*) examined how incentives affect the acceptance of EV smart charging among various groups. The research was implemented using a discrete choice experiment based on the features of 14 actual BEV smart charging programs in North America from 2020 to 2022. They found that monetary incentives are important to smart charging program enrollment but that diminishing returns exist to continued increases in payment. Another discrete choice experiment by Philip and Whitehead (*19*) conducted in Australia found guaranteed driving range can increase consumers' willingness to participate. Finally, a study by Huang et al. (*15*) on Dutch BEV owners revealed that willingness to particiapte in a V2G program increases if BEVs can be quickly recharged, making access to a level-2 charger essential for the program.

One limitation of these prior studies is that they all primarily sampled respondents from the general car owning public, with few actual BEV owners in the sample. The BEV ownership rate among the participants in the Wong et al. (*18*) study was 19%, and in the Philip and Whitehead (*19*) study it was just 1.28%, suggesting most respondents had little to no prior experience operating or charging a BEV. In contrast, in the study by Huang et al. (*15*), 99% of the respondents claimed to have driven a BEV, but their total sample was only 157 respondents.

Our research builds on this prior work through a discrete choice experiment aimed at a large sample of BEV users and owners (currently N = 858) in the U.S. All participants on our survey passed our survey checks (explained in the Methods section) that suggest they indeed own a BEV. We examine BEV owner willingness to participate in both SMC and V2G programs, taking into account both the financial benefits to customers and the operational flexibility that customers would have under different programs.

METHOD

Survey Design

We designed and fielded a nationwide discrete choice survey experiment online to quantify how different smart charging features affect BEV owners' willingness to participate in SMC and V2G programs. The survey was designed and published on formr.org, an open-source platform that leverages the R programming language to design surveys (*20*). The choice task randomization and data collection were made possible thanks to the ability to use R code in the survey. A full copy of the survey text can be accessed here: https://gwu.quarto.pub/smartchargingsurvey/.

One important design requirement was to ensure that we were indeed sampling current BEV owners. To achieve this, we began the survey with a screener section where respondents were asked to select their current vehicle make, model, and year from a drop down list of all possible vehicles in the last 30 years. We only kept responses from those who selected a BEV model, and the survey would immediately end if they picked a conventional car. Since there was no indication from the advertisement of the survey that it involved BEVs, we are confident that the respondents who filtered through truly owned a BEV as they were able to select their BEV model from a list of hundreds of vehicle models, something that is unlikely to happen unintentionally given how few of models were BEVs and because evidence shows that most Americans on average still struggle to name even one BEV model by name (*21*).

The conjoint choice questions used randomized sets of choice tasks, each containing different attributes for SMC or V2G programs. Respondents were asked six consecutive choice questions for SMC programs, and then an additional set of six consecutive choice questions for V2G programs. Each choice question included two smart charging options and a "not interested" option, meaning that respondents would prefer not to participate in the program. We leverage discrete choice models to estimate the independent value that users have towards each individual smart charging program feature. We chose 5 attributes each for the SMC and the V2G programs. Their attributes are shown in Tables 1 and 2 below.

TABLE 1 SMC Program Attributes

No.	Attribute	Range	Explanation
1	Enrollment Cash	\$50, \$100, \$200, \$300	One-time payment upon enrollment.
2	Monthly Cash	\$2, \$5, \$10, \$15, \$20	Recurring monthly payment.
3	Override Allowance	0, 1, 3, 5	Monthly frequency of freely override to normal.
4	Minimum Threshold	20%, 30%, 40%	SMC won't be triggered below this threshold.
5	Guaranteed Threshold	60%, 70%, 80%	SMC will give you this much of range by the morning.

We chose 5 attributes each for the SMC and the V2G programs. Ranges were chosen based on prior survey work (12, 18) and conversations with electric power companies.

TABLE 2 V2G Program Attributes

No.	Attribute	Range	Explanation
1	Enrollment Cash	\$50, \$100, \$200, \$300	One-time payment upon enrollment.
2	Occurrence Cash	\$2, \$5, \$10, \$15, \$20	Earning for each occurrence of V2G.
3	Monthly Occurrence	1, 2, 3, 4	Monthly occurrence of V2G.
4	Lower Bound	20%, 30%, 40%	V2G won't drain your battery below this percentage.
5	Guaranteed Threshold	60%, 70%, 80%	V2G will charge your battery back to this percentage.

See descriptions in Table 1.

Figures 1 and 2 show example choice questions for the SMC and V2G questions. In each question, the values shown were randomized according to a pre-determined experiment design, generated using the `cbcTools` R package (*22*).

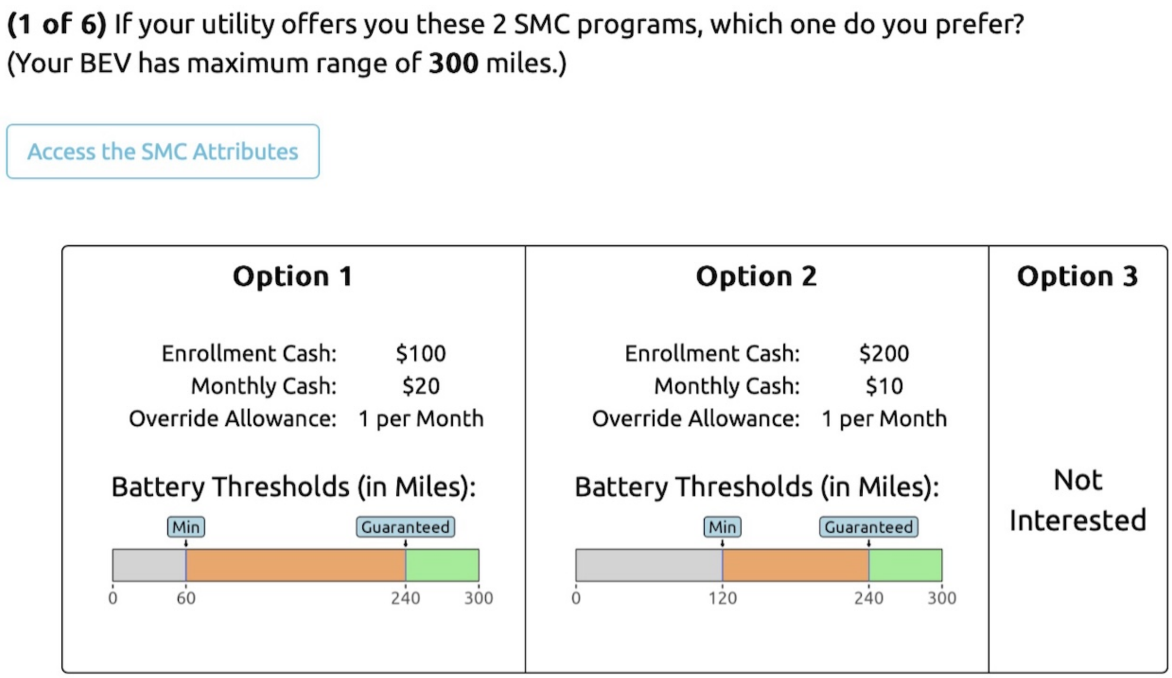

FIGURE 1 Sample SMC Conjoint Question. ***Option 1, for example, provides $100 upon enrollment, $20 per month, and an override allowance of once per month, along with a designated battery threshold. Each respondent would be asked 6 randomized choice questions.***

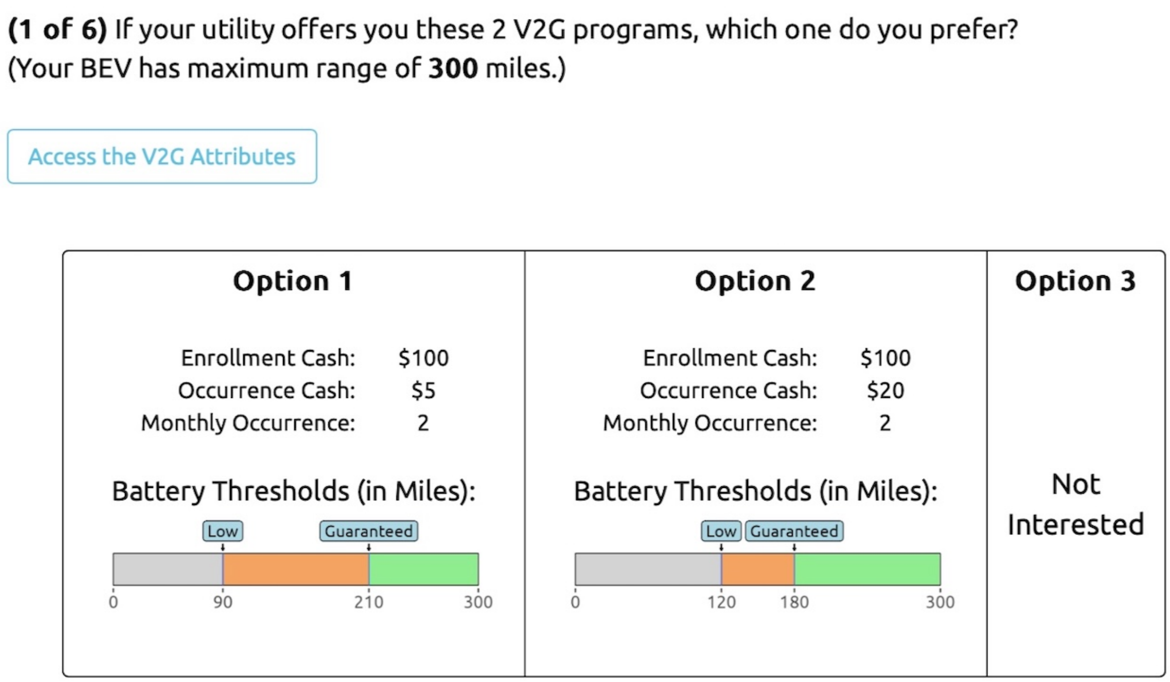

FIGURE 2 Sample V2G Conjoint Question. ***See descriptions in Figure 1, with the exception of a twice-monthly V2G event instead of an override allowance, which is a feature of SMC.***

Apart from the choice questions, there were also two other sections on BEV usage and demographic questions to capture more about the BEV owners themselves. The purpose of these sections is to explore heterogeneity in preferences across the survey sample. On average, the time respondents spent on the V2G section was 50 seconds faster than that of the SMC section.

Data Collection

Before the recruitment of the actual survey, we performed a pilot survey to assess whether people understood the questions. This was to ensure that the mechanics of the survey were working properly prior to fielding the full experiment. We proceeded with the actual survey with better confidence thanks to this pilot recruitment.

To field the survey, we posted ads on Facebook and Instagram, following ad-based survey recruitment guidelines by Kühne and Zindel (*23*), who found that social media is an effective sampling approach for identifying difficult-to-find populations. Given that BEV owners remain the vast minority of vehicle owners, they qualify as a very difficult subpopulation to find. Since Meta enables highly detailed ad targeting, we were able to focus our ads on likely BEV owners based on their selected interests. We used general keywords associated with sustainability as well as several keywords associated with specific BEV makes and models. Participants were not paid to complete the survey; we simply targeted ads towards them and asked them to take a survey. We followed our approved IRB protocol and revealed that we were a GWU research team, but we did not reveal that the survey involved BEVs or charging in order to ensure that participants would get through our initial screener section uninformed about the motive of the survey. Respondents were simply asked to complete a survey about their vehicle ownership.

The fielding began in March 2024 and is expected to last for several months until we obtain our target goal of approximately 1,500 completed survey responses. As of July 2024, we have 858 total responses, which we use in this paper to present preliminary results. Of those, 815 completed the SMC choice questions, and 414 completed the V2G questions, which was an optional section in the second half of the survey. We include a series of plots containing all demographics of the sample in a survey result summary file that can be accessed here: https://sc.pingfanhu.com/files/survey_summary.pdf.

Model Specification

We use a random utility model framework to model choice. Random utility is calculated as the sum of weighted attributes and a random error term, as shown in Equation 1:

$$u_j = v_j + \epsilon_j = \beta' x + \epsilon_j \tag{1}$$

where β is a vector of weights, x is a matrix of attributes, and ϵ_j is an error term that follows a Type 1 Extreme Value distribution (Gumbel distribution). Given this form, the probability of choosing alternative j from a set of J alternatives is given by the usual logit probability function, as shown in Equation 2:

$$P_j = \frac{e^{v_j}}{\sum_{k=1}^{J} e^{v_k}} \tag{2}$$

The SMC program contains 6 attributes: enrollment cash, monthly cash, override, minimum threshold, guaranteed threshold, and the "no choice" option. Based on Equation 1, the utility model for the SMC program is written as Equation 3 shown below:

$$u_j = \beta_1 x_j^{\text{enroll}} + \beta_2 x_j^{\text{monthly}} + \beta_3 x_j^{\text{override}} + \beta_4 x_j^{\text{min}} + \beta_5 x_j^{\text{guaranteed}} + \beta_6 x_j^{\text{no}} + \epsilon_j \tag{3}$$

The V2G program also contains 6 attributes: enrollment cash, occurrence cash, monthly occurrence, lower bound, guaranteed threshold, and the "no choice" option. Based on Equation 1, the utility model for the V2G program is written as Equation 4 shown below:

$$u_j = \beta_1 x_j^{\text{enroll}} + \beta_2 x_j^{\text{occur}} + \beta_3 x_j^{\text{monthly}} + \beta_4 x_j^{\text{lower}} + \beta_5 x_j^{\text{guaranteed}} + \beta_6 x_j^{\text{no}} + \epsilon_j \tag{4}$$

One result of the logit model is the Independence of Irrelevant Alternatives (IIA) property, which often produces unrealistic predictions in predicted probabilities between similar alternatives. To relax this assumption and explore heterogeneity in user preferences, we estimate a mixed logit (MXL) model. The MXL model accounts for variation in preferences across individuals by allowing the coefficients to vary according to assumed distributions while relaxing the IIA assumption, allowing for more flexible substitution patterns among alternatives. We use the `logitr` R package to estimate the models (*24*).

To search for a better solution and avoid local minima, we used 100 multi-starts (re-starting the algorithm from different random starting points) and simulate MXL parameter distributions using 500 Sobol draws for both the SMC and V2G programs. These outcomes are later tested with extreme values in sensitivity analysis to ensure expected behavior.

RESULTS

BEV Ownership & Demographics

The BEV ownership & demographic information are collected by single-answer choice questions. These data support the choice question results as they reveal information about the population of BEV owners in our sample. Table 3 summarizes information around BEV usage and ownership characteristics of our sample, and Table 4 summarizes personal demographic features of our sample. For a more complete summary of our sample, see our result summary file here: https://sc.pingfanhu.com/files/survey_summary.pdf

TABLE 3 Summary of Electric Vehicles

Category	Value	Count	Percentage
Car Number	1	189	22%
	2	488	57%
	3	126	15%
	4	41	5%
	5 or More	14	2%
Daily Distance	<10	193	22%
	10-30	359	42%
	31-50	182	21%
	51-100	94	11%
	>100	29	3%
	Don't Drive	1	0%
Neighbor Ownership	Own BEV	438	51%
	Don't Own	286	33%
	Not Sure	134	16%
Charge Management	App	393	46%
	SMC	52	6%
	No	413	48%
Lv2 Charger	No	137	16%
	Yes	721	84%
Tesla Ownership	No	593	69%
	Yes	265	31%
V2G Interest	No	226	26%
	Yes	632	74%
Pay for V2G Charger	Willing to	364	42%
	Don't Want	250	29%
	Already Have	18	2%
	NA	226	26%

[1] *N = 858.*
[2] *This is only a part of the electric vehicles information. For full results please refer to our online survey summary.*

Out of the 858 responses collected thus far, we see that 78% of participants own at least two vehicles and only 22% own just one vehicle. 94% of the BEV owners report that they regularly charge at home, and 46% report having some form of user-managed charging (UMC), such as using an app to control their charging, and 6% are enrolled in an SMC program.

TABLE 4 Summary of Demographics

Category	Value	Count	Percentage
Gender	Male	729	85%
	Female	114	13%
	Non-Binary	7	1%
	Not Say	8	1%
Age Group	<=30	13	2%
	31-40	66	8%
	41-50	144	17%
	51-60	235	27%
	61-70	263	31%
	>70	128	15%
	NA	9	1%
Party	NA	48	6%
	Democratic	530	62%
	Republican	77	9%
	Independent	203	24%
Climate Awareness	Not	18	2%
	Somewhat	41	5%
	Neutral	24	3%
	Believe	171	20%
	Very	604	70%
Work Status	Not Say	9	1%
	Student	6	1%
	Part-time	111	13%
	Full-time	447	52%
	Looking	14	2%
	No Job	12	1%
	Retired	256	30%
	Disabled	3	0%
Household Size	Not Say	8	1%
	1	79	9%
	2	445	52%
	3	148	17%
	4	128	15%
	>4	50	6%
House Ownership	Not Say	9	1%
	Own	800	93%
	Rent	49	6%

[1] *$N = 858$.*
[2] *This is only a part of the demographics information. For full results please refer to our online survey summary.*

For personal demographic information, 70% of the respondents report caring about the climate very much. We also find that our sample is highly skewed in gender, with 85% being male. However, a gender skew is also observed in BEV ownership in general, thus it is difficult to tell if this skew is a feature of our sampling approach or actually representative of the true BEV owner population. Additionally, 86% of the respondents self-identify as white, 53% are below the age of 60, and 51% report living in a two-person household.

Models

We initially employed multinomial logit (MNL) preference models for both SMC and V2G programs, which generated single coefficient estimates for each attribute. However, to explore heterogeneity preferences, we transitioned to mixed logit (MXL) models. The final SMC model is presented in Table 5 below. The mean utility value for the "No Choice" option of the SMC program is 5.52, suggesting that respondents on average prefer not to participate in a SMC program, all else being equal.

TABLE 5 SMC Model Coefficients

Attribute	Coefficient	Distribution	Type	Estimate	Std Error
Enrollment Cash	β_1	log-normal	μ	0.0043	0.1173
		log-normal	σ	1.3187	0.1149
Monthly Cash	β_2	log-normal	μ	0.1045	0.0827
		log-normal	σ	1.2127	0.0991
Override Allowance	β_3	normal	μ	0.3259	0.0224
		normal	σ	0.2755	0.0305
Minimum Threshold	β_4	normal	μ	0.0135	0.0044
		normal	σ	0.0449	0.0055
Guaranteed Threshold	β_5	normal	μ	0.0715	0.0046
		normal	σ	0.0257	0.0032
No Choice	β_6	normal	μ	5.5186	0.3964
		normal	σ	1.5755	0.2552

[1] *This model shows the utility of each attribute with 1 unit of increment of its value. For example, monthly cash has a coefficient of 0.1045, meaning with $1 more of monthly cash, the customer utility will increase by 0.1045.*

[2] *MXL models require an assumed random parameter distribution for each random feature. We use both normal and log-normal distributions.*

The final V2G model is presented in Table 6 below. The utility value for the "No Choice" option of the V2G program is 5.42, again indicating that respondents on average prefer not to participate in a V2G program, all else being equal.

TABLE 6 V2G Model Coefficients

Attribute	Coefficient	Distribution	Type	Estimate	Std Error
Enrollment Cash	β_1	log-normal	μ	0.0065	0.1397
		log-normal	σ	1.3575	0.1326
Occurrence Cash	β_2	log-normal	μ	0.1732	0.0774
		log-normal	σ	0.6890	0.0943
Monthly Occurrence	β_3	normal	μ	0.3122	0.0549
		normal	σ	0.5045	0.0803
Lower Bound	β_4	normal	μ	0.0748	0.0076
		normal	σ	0.0564	0.0092
Guaranteed Threshold	β_5	normal	μ	0.0488	0.0066
		normal	σ	0.0340	0.0067
No Choice	β_6	normal	μ	5.4156	0.6699
		normal	σ	3.0122	0.5083

See descriptions in Table 5.

Sensitivity

While the estimated coefficients are difficult to directly interpret (utility is an abstract value that can only be compared in a relative sense), they do indicate the relative strength of changes in attribute values in affecting user preferences. To make the results more easily interpretable, we generate sensitivity plots of changes in user enrollment due to changes in each feature based on the MXL models. Two sets of sensitivity analyses were conducted and illustrated as sensitivity plots and tornado plots, where sensitivity plots reveal the sensitivities of single attributes and tornado plots show all five attributes together. In each simulation, we compare the percent of respondents that are predicted to opt in to the smart charging program compared to opting out (i.e. choosing the "no choice" option).

In these simulations, we chose a baseline simulation for each smart charging program against which to compare all other simulation results. For the SMC program, the baseline is defined as \$50 Enrollment Cash, \$5 Monthly Cash, 1 time Override, and 20%/50% battery thresholds (minimum and guaranteed states of charge). For the V2G program, the baseline is defined as \$50 Enrollment Cash, \$5 Occurrence (Event) Cash, 1 time Monthly Occurrence, and 20%/50% battery thresholds.

The sensitivity plots, as shown in Figure 3, illustrate the sensitivity of each attribute in the smart charging programs. The curves form an "S" shape if expanded to a wider range, which is the expected shape for logit models. In these plots, the solid lines indicate predictions within the ranges of features included in our survey and the dashed lines indicate predictions made beyond the range of levels shown on the survey. For example, for the SMC program, the Enrollment Cash included a range from \$50 to \$300, but in the plot it is expanded from \$0 and \$1000.

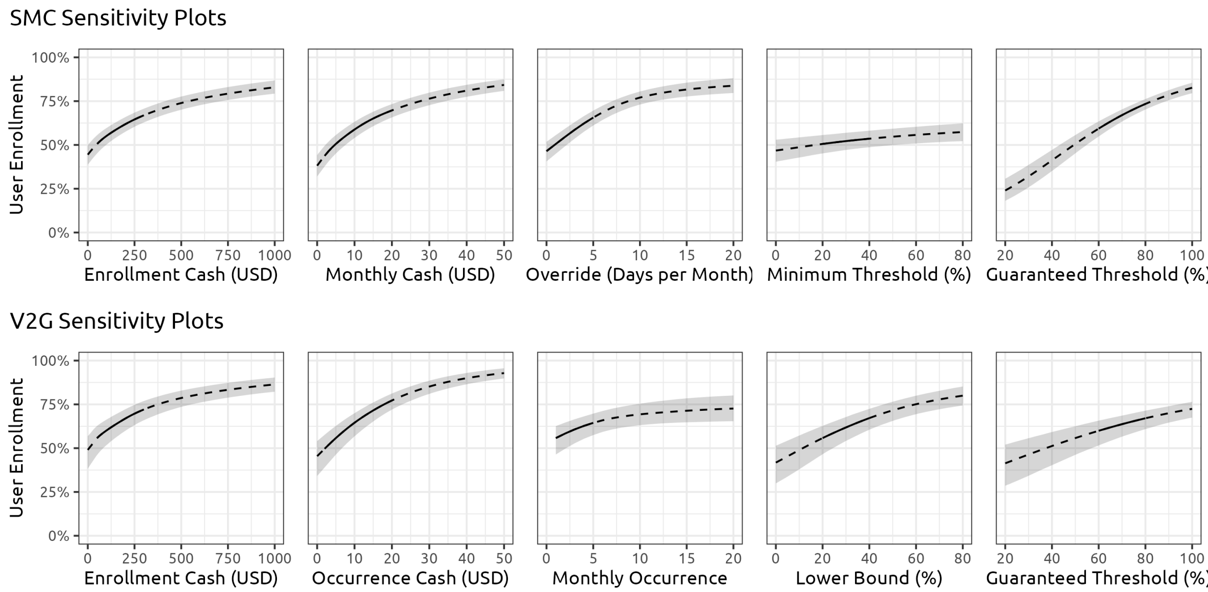

FIGURE 3 SMC & V2G Sensitivity Plots

The sensitivity plots reveal the relative level of sensitivity BEV owners have towards changes in each feature. These slopes provide a preliminary indication of the "importance" of each attribute. For instance, monetary incentives demonstrate a noticeably higher sensitivity compared to other attributes in both smart charging programs. Specifically, in the case of SMC, the Monthly Cash feature appears to be particularly sensitive as small changes in the attribute can lead to larger changes in enrollment.

We use tornado plots to more systematically compare the differences across each feature. In a tornado plot, all attributes are compared together and ranked in descending order based on their relative sensitivity in terms of the magnitude of changes in the predicted enrollment. We have generated tornado plots for both the SMC and V2G programs. Each plot displays negative and positive sensitivities, colored in orange and blue, respectively. The vertical axis represents the five attributes while the horizontal axis shows the probability of user enrollment as each attribute varies, with others remaining at their baseline values.

Here is an example of interpreting the SMC tornado plot. Again the baseline is \$50 Enrollment Cash, \$5 Monthly Cash, 1 time Override, and 20%/50% battery thresholds. The user enrollment for this baseline is about 51%, as indicated in Figure 4, where you can see a clear vertical line at user enrollment being 0.51 that separates the 5 bars as orange to the left, and blue to the right. Guaranteed Threshold, as the most sensitive attribute, is placed on the top. With other 4 attributes staying at baseline, a 40% guaranteed threshold will result in about 42% user enrollment, which grows to about 74% if guaranteed threshold increases to 80%. The same logic is true for the rest 4 attributes. Minimum Threshold is the least sensitive attribute which doesn't produce significant effect on user enrollment. The V2G tornado plot can be interpreted in the same way, with baseline defined as \$50 Enrollment Cash, \$5 Occurrence (Event) Cash, 1 time Monthly Occurrence, and 20%/50% battery thresholds, as indicated previously.

For the SMC program (Figure 4), the attribute with the highest sensitivity is Guaranteed Threshold, which could be the result of range anxiety, a frequently-cited concern among BEV owners. Monthly Cash and Enrollment Cash are also important, suggesting the necessity of financial incentives in driving enrollment. However, Monthly Cash as a form of recurring cash back could be more costly to utilities than Enrollment Cash as a one-time payment. Override is somewhat sensitive due to the fear of uncertainty. Minimum Threshold is least sensitive of all.

In the V2G program (Figure 5), however, participants prioritize the monetary returns, with Occurrence Cash being more significant than Enrollment Cash. The two attributes of remaining battery are right after the monetary attributes, again suggesting a potential concern over range anxiety. Monthly Occurrence is ranked lowest, possibly due to concerns about battery degradation from increased charging cycles.

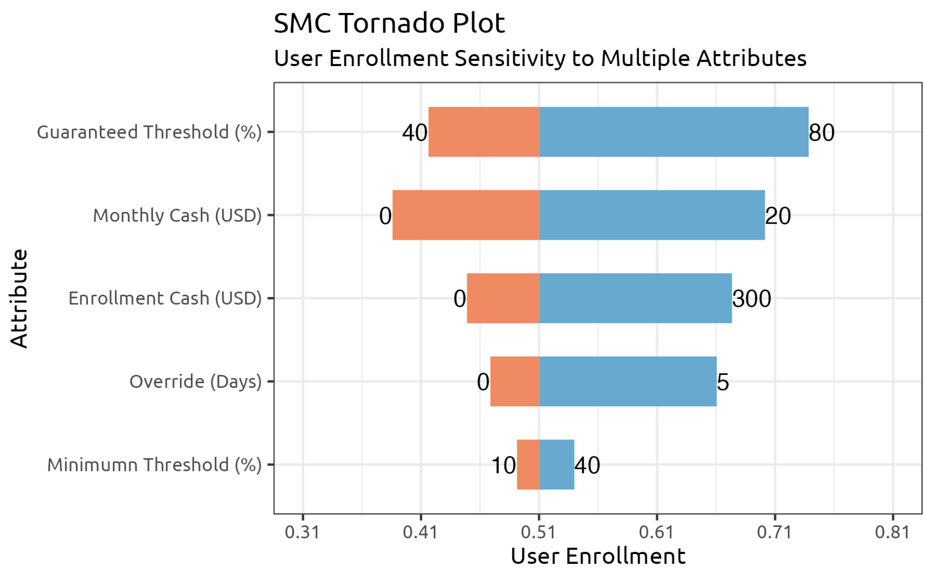

FIGURE 4 SMC Tornado Plot

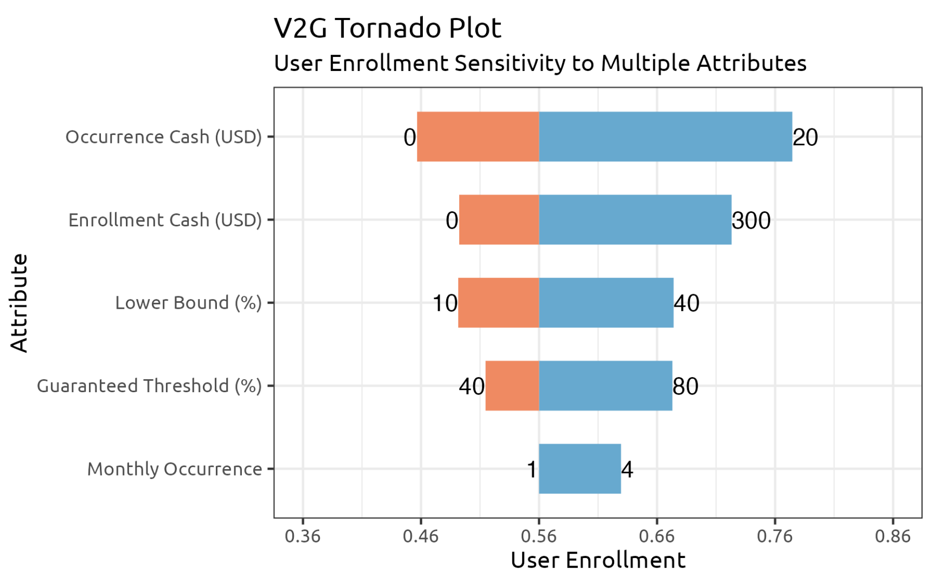

FIGURE 5 V2G Tornado Plot

Simulations

While comparing the sensitivity to individual program feature can be informative, the ultimate goal of this study is to understand which *combination* of smart charging program features for both SMC and V2G that lead to higher overall enrollment. To assess this, we run a series of simulations comparing specific smart charging programs against the no choice option. The simulation results illustrated in Figures 6 and 7 reveal the results.

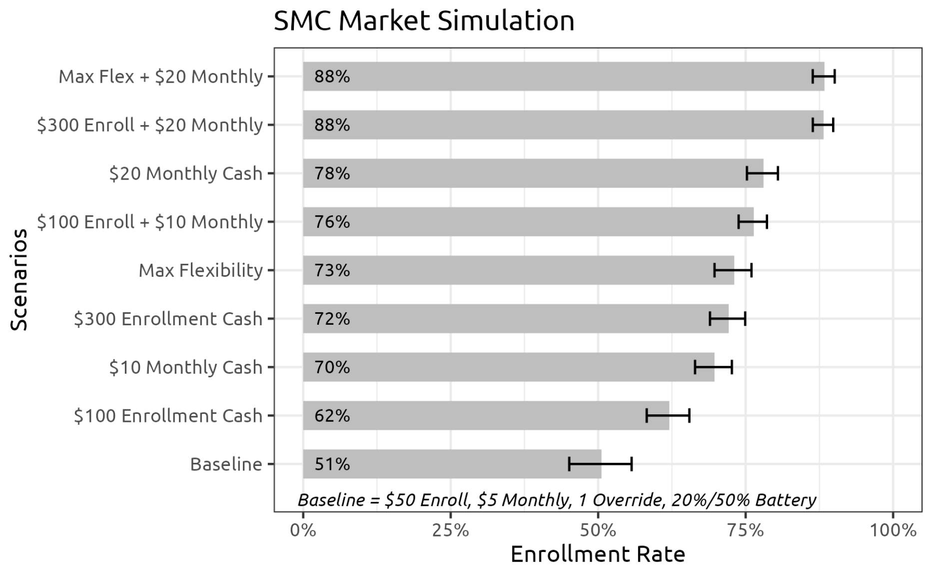

FIGURE 6 SMC Market Simulation. ***We start with the baseline and increase the flexibility or monetary incentives. The enrollment rate increases as expected, and correlates with the tornado plot, but the key is to find a relatively high enrollment with a reasonable cost.***

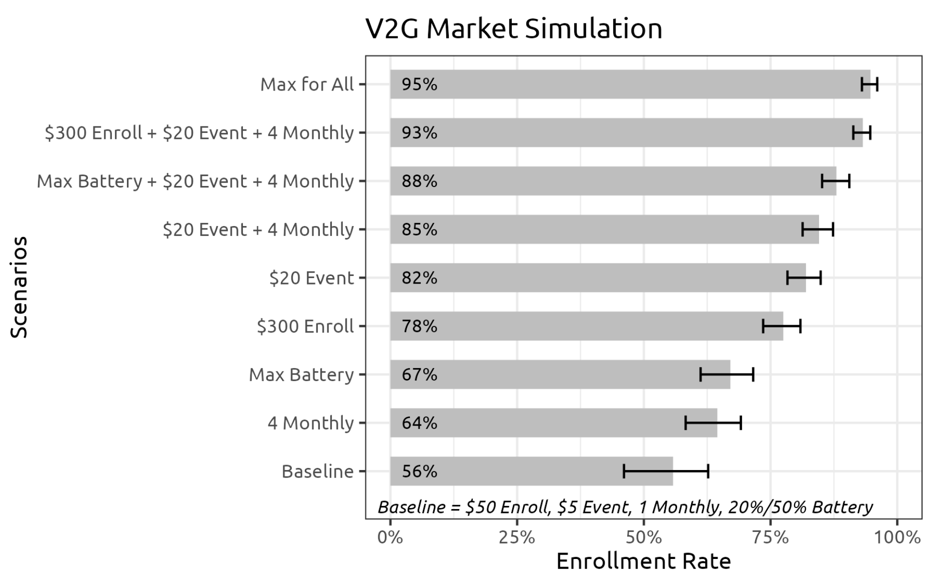

FIGURE 7 V2G Market Simulation. ***See descriptions in Figure 6.***

DISCUSSION

By conducting a discrete choice experiment with actually BEV owners, we have contributed new understandings about BEV owners' willingness to participate in both SMC and V2G smart charging programs. According to our sensitivity analyses, the most influential attributes of SMC programs are Monthly Cash and the Guaranteed Threshold, as shown in the tornado plot in Figure 4. It is reasonable that Monthly Cash is more important than a one-time Enrollment Cash as this is a recurring payment whereas the Enrollment Cash in a one-time payment. This is consistent with prior real-world trials where researchers found that the overall participation rate for participants in a trial SMC program fell once the recurring payment was reduced or removed (*17*).

We also know that range anxiety is a major concern for BEV users (*25*), which aligns with the finding that the Guaranteed Threshold for the battery state of charge is an important feature for BEV owners. In contrast, the minimum threshold is the least important feature, suggesting that users are willing to allow smart charging to begin even at low battery charge levels, so long as the utility can guarantee a sufficient charge by morning.

Likewise, as shown in the tornado plot of Figure 5, the most influential attributes for V2G programs are Occurrence Cash and Enrollment Cash. A reasonable explanation is that V2G is a way for owners to use their BEVs to earn money. That is, in contrast to SMC which could be occurring at any point in time, V2G discharge events are likely less common and present themselves as an opportunity for a BEV to earn money on a case-by-case basis. Another interesting finding is that although only 74% of respondents chose to answer the V2G section of our survey, for those that did answer it we see an overall higher baseline participation rate compared to that of SMC.

Finally, as shown in Figure 6, in the SMC simulation we can see that the enrollment rate is 78% by providing \$20 monthly cash, starting from which, providing a \$300 Enrollment Cash gives 10% more and will result in 88% of enrollment. Since adding max flexibility provides the same 88% enrollment as adding \$300, we can have a reasonable judgement that sacrificing \$300 as Enrollment Cash efficiently hedges the necessity of providing more flexibility.

The V2G simulation, shown in Figure 7, shows a straight-forward connection between the incentives and willingness to participate. Here, monetary incentives surpass the other attributes, and a full course of monetary combination (high Enrollment Cash, high Occurrence Cash, and high number of monthly occurrence) results in the highest enrollment rate of 93%, and this is really close to the best attributes results of 95%. In participants' view, since V2G is a process of trading their BEVs' usability with monetary income, they are highly sensitive to monetary returns. Out of this complicated result, a simple conclusion regarding the V2G program is that the success of the V2G program highly depends on the budget from the utility suppliers. To be more specific, if the utility suppliers can save enough money by operating a V2G program to pay respondents a sufficient reward for participating, then this program is more likely to succeed and result in a virtuous economic cycle.

Since the study is still in progress, the limitations are mainly in the amount of data, which in its current state limits a more fine-grained comparison of preferences across different subgroups in the population. Future work will collect more data and integrate models of consumer preference into grid simulations to estimate the benefit-cost trade off for implementing different smart charging programs from the perspective of utilities.

CONCLUSION

This study explores the willingness of BEV owners to enroll in different smart charging programs. The purpose of smart charging is to allow utilities control over BEV charging to align it with grid supply and demand to achieve lower emissions and facilitate greater use of renewable energy sources. We consider two forms of smart charging: SMC in which utilities control charging timing and duration, and V2G in which bidirectional charging can occur to serve the grid. We use a discrete choice survey experiment to measure the preferences of BEV owners to enroll in these programs. While we plan to recruit 1,500 respondents, we present results for our current total of 858 to date. The responses revealed valuable demographic information regarding BEV ownership and usage. We used the choice data results to estimate mixed logit (MXL) models and conducted sensitivity analyses based on the models of both SMC and V2G programs. We found that guaranteed driving ranges during smart charging events and continued payments for enrolling in the programs are the two more important features of smart charging programs. Based on the sensitivity results, we conducted market simulations and revealed trade-offs between these important features. With more data, we will be able to provide more information about preferences for different subgroups of interest.

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