Reducing winter peaks in electricity consumption : a choice experiment to structure demand response programs

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Reducing Winter Peaks in Electricity Consumption:

A Choice Experiment to Structure Demand Response Programs

Abstract

Winter peaks in Belgian electricity demand are significantly higher than the summer peaks, creating a greater potential for imbalances between demand and supply. This potential is exacerbated because of the risk of outages in its ageing nuclear power plants, which are being phased out in the medium term. This paper conducts a choice experiment to investigate the acceptability of a load control-based demand response program in the winter months. It surveys 186 respondents on their willingness to accept limits on the use of home appliances in return for a compensation. Results indicate that respondents are most affected by the days of the week that their appliance usage would be curtailed, and by the compensation they would receive. The willingness to enroll in a program increases with age, environmental consciousness, home ownership, and lower privacy concerns. The analysis predicts that 95% of the sample surveyed could enroll in a daily load control program for a compensation of €41 per household per year. Thus while an initial rollout among older and more pro-environment homeowners could be successful, a wider implementation would require an explanation of its environmental and financial benefits to the population, and a greater consideration of their data privacy concerns.

Highlights

- We conduct a choice experiment to design a demand response program in Belgium
- People care about the days per week that the program will run and the compensation
- The willingness to enroll changes with age, home ownership, environmental awareness

- 95% of the sample can be predicted to enroll for under €41 per household per year

Keywords:[1] Demand response; Smart appliance; Residential electricity; Stated preferences; Discrete choice experiment; Load control

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[1] Abbreviations: Demand response (DR); Discrete choice experiment (DCE); European Commission (EC); Gigawatt (GW); Gigawatt-hour (GWh); Hierarchical Bayes (HB); Information and communication technology (ICT); Kilowatt-hour (kWh); Likelihood Ratio (LR); Megawatt (MW); Megawatt-hour (MWh); Multinomial logit (MNL); Nuclear power plant (NPP); Panel mixed logit (PML); Renewable energy (RE); Time of use pricing (ToU); Willingness to accept (WTA)

1. Introduction

The electricity sector generates up to 30% of global greenhouse gas emissions [1]. At the same time, increasing electricity consumption – coupled with an ageing grid infrastructure – presents a challenge for energy security. Demand response (DR) programs, which aim to shift demand for electricity through incentives such as variable pricing and controlling appliance loads so that this demand better matches with supply, are a potential avenue to aid with the grid integration of renewables, and with improving energy security [2][3]. The European Commission (EC) estimates a total response potential of 160 gigawatts (GW) by 2030, with 40% of this potential flexibility coming from the residential sector [4]. DR is thus being promoted through enabling policy frameworks and trial programs in many European countries, particularly in the residential sector [5].

However, the introduction of DR in the residential sector has had mixed results. Some studies have found their implementation to be successful. For instance, Bartusch et al's empirical study [6], Faruqui and Sergici's survey [7], and a UK government review of DR trials [8], all found that households do respond to pricing signals. The Irish energy regulator [9] further found that higher-consuming households delivered greater reductions. However, other research has yielded conflicting findings and suggested that consumer attitudes have limited the responsiveness to DR programs [10]. For instance, Gyamfi et al [10] stated that a high number of households – particularly the richer ones – did not actually respond to price signals. Consumers were found to be less price-sensitive when they were more concerned about convenience, comfort, privacy, and safety [11][12][13]. Hall et al [14] identified that households want more information on the potential benefits of DR. Similarly, Brent et al [15] stated that knowledge about consumption, and the presence of enabling technology, can increase the effectiveness of time-varying pricing.

This suggests that household preferences are not homogenous and can depend on the structure of the DR program. Further, Srivastava et al [16] found that the success of DR programs can also be related to the socio-economic contexts around their implementation.

Though there is an increasing focus on understanding contextual consumer preferences, and determining how they affect response to DR programs, existing research has made limited use of stated preference approaches such as discrete choice experiments (DCEs). In current literature, Ericson [17] conducted a discrete choice analysis using opt-in data from a critical peak pricing (CPP) experiment in Norway, to understand the bases on which consumers choose between tariffs. Buryk et al [18] ran a labelled DCE, using convenience sampling and varying only the price attribute, to determine whether disclosing the environmental and system benefits of dynamic tariffs could increase customer adoption. Also Pepermans [19] ran a DCE with snowball sampling to assess the extent to which consumers in Belgium would use smart meters, although the design did not include dynamic pricing schemes. Other studies [20][21][22][23] have used DCEs to understand preferences for other aspects of electricity generation and provision.

Current choice modeling applications have not focused however on the actual structuring of DR programs; such an approach would allow the estimation of a monetary value of the different attributes of DR programs, thereby helping better structure such programs.

1.1 Opportunity for Demand Response in Belgium

There is a potential in Belgium for implementing DR in the residential sector, and the national transmission operator is exploring ways to reward flexibility with lower energy bills [24]. Such flexibility is particularly important during the winter months for two reasons. First, electricity demand peaks in the winter months, reaching about 12,000-14,000 megawatts (MW), and is about 2,000 MW higher than in the summer [25][2].

Second, Belgian generation has been largely reliant upon its ageing nuclear power plants (NPPs) – Figure 1 shows the country's shares of installed power. Between 2010 and 2014, generation fell by 24% because of outages at its NPPs [25], but it has since rebounded.

Figure 1: Shares of Installed Power in Belgium in 2019

Although Belgium will phase out its NPPs over the medium to long term [27][28], there is a short- to medium-term risk to the security of supply due to the possibility of further outages, particularly during the winter months. Reducing winter peaks in demand would reduce the need for costly peaking generation and would also help manage the markets in case of such outages.

1.2 Scope of Paper

This paper uses a stated preference approach to estimate a monetary value, to consumers, of different attributes of DR programs. It conducts a DCE in the Belgian region of Flanders to gauge respondents' willingness to enroll in a winter DR program in return for a monetary

[2] The residential sector comprised about 23.1% of total consumption [25]

compensation. In this way, the paper examines consumer preferences for electricity contracts in the Belgian context. The contributions of this paper are: (a) unlike earlier approaches to structuring DR programs, it attempts to do so by taking consumer preferences into account in a well-defined and quantifiable way, (b) to our knowledge, it is among the first papers that uses a DCE to study consumers' willingness to shift electricity consumption based on various DR program attributes, in particular by using policy simulations, and (c) it addresses a clear opportunity for significant policy relevance since Belgian authorities are actively considering implementing residential DR programs. Thus, the paper fills critical gaps in research with its aim to aid in structuring a Belgian DR program that could reduce the winter peaks in electricity demand in the short to medium term.

2. Methods

2.1 Discrete Choice Experiments

DCEs are used to study people's preferences for various attributes of products or services in fields such as marketing, transport, health economics, and environmental economics. They are an attractive tool to value non-market goods and services, or to derive their non-consumptive values.

A DCE offers respondents several choice sets, with a number of alternatives in each choice set, where each alternative is a combination of levels of different attributes. For each choice set, respondents indicate the alternative they like better. The most statistically efficient design is determined by means of the Bayesian D-optimality criterion [29]. Such a design guarantees that all parameters can be estimated with maximal precision.

DCEs rely on the assumption that choices between alternative options reflect the utility that accrues from those alternatives, as derived from random utility theory [30]. This framework states that the utility U_j associated with an alternative j is the sum of its systematic and random components:

$$U_j = V_j + \varepsilon_j = x'_j\beta + \varepsilon_j \quad (1)$$

where V_j is the indirect utility function of alternative j, x_j is the vector describing the attribute levels of alternative j, β is the vector of preference parameters representing changes in utility arising from changes in the attribute levels, and ε_j is the stochastic error term.

The basic model used to analyze choice data is McFadden's [31] multinomial logit (MNL) model. Given a choice set with J alternatives, the probability that an individual i ϵ {1,..., N} in the sample chooses alternative k is defined as :

$$P_{ik(MNL)} = \exp(x'_{ik}\beta) / \Sigma^{J}_{j=1} [\exp(x'_{ij}\beta)] \quad (2)$$

The MNL model is restricted in that preferences are assumed to be homogenous across respondents. Therefore, current modeling practice has shifted toward the more flexible panel mixed logit (PML) model that accounts for heterogeneous preferences across respondents and correlation across repeated choices from the same respondent [32]. This model assumes a distribution of preference weights across the sample, reflecting the preference heterogeneity. This means that, unlike the MNL model, which estimates only the mean preference effect of an attribute level, the PML model also yields a subject standard deviation denoting the individual variation around it. Formally, the mixed logit probabilities are the integrals of standard logit probabilities over a density of random parameters, denoted by

$$P_{ik(PML)} = \int P_{ik(MNL)}.f(\beta).d\beta \tag{3}$$

where f(β) is a density function. To estimate the random parameters, we use the hierarchical Bayes (HB) technique in the JMP Pro 14 software under the assumption of normally distributed preference parameters without correlation between attributes. These estimated random parameters model the unobserved heterogeneity in the respondents' preferences.

The marginal willingness to accept (WTA) a compensation for an attribute A, if utility is linear in the preference parameters, is measured as its preference weight divided by the marginal utility of money M, where the latter is the negative of the preference weight of the payment attribute. This is shown as:

$$WTA_A = \beta_A / (-\beta_M) \tag{4}$$

Lastly, for the policy simulations conducted in Section 3.3, which are based on the PML model estimates, we apply the approach used by Bennett et al [33]. In these simulations, we estimate the predicted enrolment probability in a DR program k for respondent i in the sample by the binomial logit characterization:

$$P_{ik(Enroll)} = \exp(x'_k\beta_x + z'_{ik}\beta_z) / [1 + \exp(x'_k\beta)] \tag{5}$$

where β_x is the vector of main-effect attribute parameters, β_z is the vector of user-specific parameters, and z_{ik} is the vector of user-specific variables. We then estimate the minimum payment c_k for program k as the level of compensation at which the model predicts a targeted enrolment rate of R:

$$\Sigma^{N}_{i=1} F [P_{ik(Enroll)} \mid c_k] / N = R \tag{6}$$

where F [.] takes a value of 1 if $P_{ik} > 0.5$, and 0 otherwise. For the policy simulations, we estimate c_k for various values of R, i.e., we estimate the minimum payments necessary to predict various enrolment rates of sample households.

2.2 Background Literature and Consultations

In Belgium, a DR trial called Linear had secured the participation of 240 families in the region of Flanders, 54 of whom were introduced to time-of-use (ToU) pricing while the remaining 186 were provided with three smart appliances: washing machines, dishwashers, and tumble dryers[3]. The results revealed that response to the ToU pricing was weak, while the response to the smart appliance program was higher – an extrapolation of the results to the entire Belgian population suggested a potential of up to 280 MW of flexibility [34][35].

Drawing upon these results, we chose to adopt a design based on smart appliances, rather than on time-based pricing of electricity. For linguistic and cultural consistency, we focused our study on Flanders. In designing the experiment, we consulted various experts, including representatives of the Flemish energy regulator (VREG) and environmental ministry (LNE).

[3] These smart appliances had a delayed start option – families were allowed to configure the start of their appliances at any time but with a maximum programmable delay of 24 hours, so long as they finished their cycles before the given deadlines. The participants received a fee for the flexibility they offered

Since we could not consider heating systems, as they are largely powered by natural gas in Belgium and not by electricity [36], we focused on the same three appliances that were successfully used in the Linear trial, i.e. washing machines, dishwashers, and dryers, which are together responsible for 28% of household electricity use [37].

For the hypothetical DR programs in the DCE, we assumed that the appliances would have the ability to be externally controlled, using controllers installed on these appliances, for a few hours per day. We selected the numbers of hours in which appliance loads could be controlled based on the average electricity load curves for Belgium [38] – the average daily load curves during the winter months of three years are shown in Figure 2.

Figure 2: Average daily load curves, 1 January – 31 March

For the compensation, we determined that the annual average household electricity bill in Flanders was approximately €1000 [40], implying that the average monthly bill would be in the range of €80-€85. We then aimed to offer respondents amounts in the range of 10-30% of an average monthly bill as total compensation across the annual duration of the program.

2.3 Pilot DCE

Based on these inputs, we first conducted a pilot experiment consisting of 8 choice tasks, each task offering two hypothetical DR programs. The structure and purpose of the DR program was explained to respondents before they were presented with the choice sets. Respondents who did not own a washing machine were not considered eligible for the DCE. Besides the two alternative programs, each choice set also included a 'no-choice option' allowing respondents to opt out from any of the presented programs and stay with their current consumption pattern.

The pilot DCE questionnaire was circulated among author networks, and obtained 47 usable responses in total. The initial results indicated that only the parameter estimates for the number of hours per day that appliances would be controlled, and the compensation required, were statistically significant. Notably, the no-choice parameter was found to be significant in the pilot results, indicating either that respondents' utilities increased by choosing not to choose, or that respondents did not find any of the alternative DR programs appealing.

2.4 Main DCE

The design of the main DCE was thus informed by (1) secondary research into the Belgian electricity market, (2) lessons from the Linear trial, (3) consultations with electricity sector experts, and (4) results from the pilot DCE. The attributes and their levels used in designing the choice sets for the main experiment are laid out in Table 1, where the levels are listed in increasing order of their expected preference.

Table 1: Main DCE - Attributes and Levels

As in the pilot phase, owning a washing machine was a minimum criterion to participate. For the attribute 'Appliances that would be controlled,' in order to avoid splitting the sample based on appliance ownership, we asked the respondents to assume that they owned all three appliances.

We brought down the number of choice sets in the survey from 8 to 6, to reduce the risk of respondent fatigue, which could have partly contributed to the selection of the 'no-choice' option in the pilot testing. Accordingly, we generated a Bayesian D-optimal design of 12 choice sets using different combinations of the attribute levels in Table 1. The design is Bayesian because it includes prior knowledge about the parameters in the form of a parameter distribution in the design process [29]. We divided the 12 choice sets into two surveys – a sample choice set is shown in Figure 3. In determining the prior parameter distribution, we drew on the parameter estimates from the analysis of the pilot data. We generated the Bayesian design using the JMP 14 software.

Figure 3: Sample Choice Set Used in Main DCE

The structure and purpose of the DR program was again explained to respondents before they were presented with the choice sets. As in the pilot DCE, respondents were given the option to remain with their current consumption structure. The choice experiment was accompanied by questions on appliance operation, as well as on respondents' tariff structures and billing amounts. A separate section captured demographic information on age, gender, income, education, and dwelling characteristics. Additional questions were included to gauge respondents' attitudes towards data privacy, environmental issues, and new technologies. In order to encourage respondents to fill out the survey, we offered to donate €0.50 to a charity of their choice upon their completion of the questionnaire.

To reach out to respondents, the questionnaire was disseminated online through Qualtrics. As it was conjectured that younger, well-educated households would be more accepting of smart appliances, we decided to aim at an oversampling of these segments[4]. We thus circulated the survey among (1) authors networks, (2) different residential community groups in Flanders via Facebook, (3) families that had participated in the Linear trial, (4) university students, and (5) a Flemish organization working on sustainable technologies.

The survey ran from July until early October 2018, and generated 186 usable responses in total. These were analyzed separately from the 47 responses in the pilot phase, owing to modifications in the attributes and levels.

3. Results

3.1 Respondent Characteristics

Descriptive statistics of the 186 respondents are listed in Table 2. As expected, the sample is younger and better educated than the overall population, although there is a slight underrepresentation of females.

Table 2: Respondent Characteristics Relative to Belgian Population

Possibly owing to the sample's demographic profile, the respondents were also very comfortable sharing additional data with their electricity provider and using new technologies, and indicated behaving in an environmentally-conscious way.

[4] Expert consultations corroborated that since typical DR rollouts proceed in a phased fashion, obtaining a sample that consists of early adopters who are more likely to embrace such program would yield more valuable findings, rather than a broader sample that might yield less information.

3.2 Modeling Results

Across the 1116 choice sets presented to the final sample, respondents chose the 'no-choice' option 206 times, or in 18.4% of the cases, down from 36.9% in the pilot DCE. This suggests that the DR programs in the revised design offered greater utility, either in terms of their increased desirability or in terms of the reduced cognitive burden to respondents, or both.

With the attributes coded as continuous variables, except "Appliances controlled," which was coded as ordinal, we first obtained the PML parameter estimates and significances for the main effects.

The results suggested that respondents are primarily concerned with the days of the week that a DR program would run, and with the compensation they would receive for their flexibility. A greater number of load control days per week would reduce their utility from the program and would increase the compensation required.

We then refined the model by omitting the insignificant attributes and estimating subject effects, and tested a number of alternative model specifications for significance and goodness of fit. The final model with the best fit is summarized in Table 4.

Table 4: Parameter Estimates and Goodness-of-Fit for Overall Model

When we calculate the willingness to accept compensation using Equation 4, then on average, for each extra day of the week that the DR program runs, respondents would need to be compensated an additional €2.25. Also, respondents attach a higher utility to participating in such program than to staying on the current tariff structure.

However, these findings are not uniform, and vary with respondent profile. For instance, for a given number of days per week that the program would run, older respondents required a lower compensation than younger respondents. While this initially seemed counter-intuitive, it may be because some of the respondents were university students and might have been more mindful of financial constraints.

Female respondents generally required a lower compensation to participate in the DR program than male respondents, suggesting that the latter might care relatively more about pricing while the former might be driven more by non-price factors. This may be associated with the fact that 44% of male respondents reportedly earned more than €4000 per month, compared to the sample average of 34%.

Respondents who undertook more environmental actions – and were by extension assumed to be more environmentally conscious – were more willing to participate in the DR programs than those who undertook fewer environmental actions, as would be expected. Similarly, respondents who owned and lived in their own dwellings required a lower compensation to participate in the programs than those who were renting their dwellings, which may be linked to a sense of ownership and responsibility, or to greater levels of income security.

Lastly, respondents who were more comfortable sharing additional information with their electricity providers – and thus exhibited lower privacy concerns – were less likely to remain on their current tariff structures.

Other factors, such as levels of education, comfort with technologies, and income were not found to be significant in this analysis. This might be due to the sample being biased towards highly educated respondents, or due to a limited sample size. Alternatively, it suggests that DR programs may have more widespread acceptance than would be intuitively expected, which can be validated through future research.

Since the sample is younger and somewhat gender-skewed compared with the overall Belgian population, we expect that, taking these subject effects into account, the average utility of the population from a DR program might be higher than that of the sample. However, we are unable to estimate the overall population concerns with privacy and the environment, both of which could more than offset the age- or gender-based increases in average utility.

3.3 Policy Simulations

Based on the parameter estimates from the final model in Table 4, we highlight the levels of compensation required to achieve predicted sample enrolment rates of 80%, 90%, and 95% for the various numbers of days per week that a smart appliance-based DR program could be implemented. They appear in Table 5.

Table 5: Policy Simulations based on Overall Model Results

Figure 4 shows how predicted sample enrolment rates vary with varying levels of compensation offered.

Figure 4: Enrolment Rates at Various Levels of Compensation

A few observations are of particular interest. First, we notice that about 30% of the sample would enroll in a DR program without requiring any compensation. These respondents might be very favorably disposed towards DR, and/or may have prior experience with it (such as the Linear participants). Second, at higher enrolment rates and for a greater number of days, the required compensation levels increased at an increasing rate, understandably indicating higher resistance to such programs for a smaller proportion of the sample. Lastly, taking this further, we were unable to reach a predicted 100% enrolment rate with these simulations, suggesting that some respondents would be completely unwilling to accept a DR structure.

We note however that actual enrolment rates might vary, for instance, by whether the 2 days-a-week program runs on weekdays or on weekends. The simulations could not distinguish between preferences for days of the week. However, if full enrolment is not a strict goal for the short term, even high levels of sample enrolment – 90% or 95% – can be predicted for a daily program at compensations of €22-€41 per household per year. Longer term strategies can then address the barriers to full enrolment.

3.4 *Economic Benefits of Demand Response Implementation*

If we expect that the winter peak in Belgian electricity consumption is about 14,000 MW [25] and that the residential sector accounts for 30% of this peak[5], then the residential sector can be expected to have a peak demand of approximately 14,000 x 30% = 4,200 MW. In the winter months, demand peaks between 5pm and 8pm in the evenings [38], presumably when most people get home from work.

[5] It accounts for 23.1% of total annual consumption, as mentioned in Section 1.1, but we expect that its share of peak demand is higher [47][48][49]

We now assume a full population enrolment in a DR program, independently of the policy simulations in Section 3.3. Given that the three appliances covered in this study constitute 28% of household usage [37], we assume a willingness to be flexible with half of these appliances (or 14% shifts in total household electricity use) at any point in time, given that not all of them are likely to be used simultaneously. This could lead to up to 14% x 4,200 = 590 MW of flexibility realized at peak times. This constitutes 4.2% of the overall peak.

If we further assume that this flexibility can be sustained across a DR program that runs for 3 hours per evening, 7 days per week, and 24 winter weeks per year, then the total annual flexibility delivered can be roughly estimated as 590 x 3 x 7 x 24 = 297,400 MWh. These numbers for peak and total annual shifts are based on optimistic estimates of household flexibility; however, they are more likely to be realized if more appliances are covered and/ or electricity were the primary energy source for space and water heating.

With an average price of electricity in the short-term wholesale markets of €45/MWh, the gross value of this flexibility to the system works out to 297,400 x 45 = €13,380,000 per annum. The actual net benefits would however depend on the differences in the exact hourly prices in the wholesale markets, and we therefore do not estimate these benefits here.

However, with about 4.9 million households in Belgium [50], and an average electricity price of 28 euro cents per kWh [51], this also works out to an economic value of 297,400,000 x 0.28 / 4,900,000 = €17.00 per household per annum. It may be noted that this value is again dependent on the appliances covered, and only represents reductions – not shifts – in consumption. We cannot estimate potential household savings because (a) Belgium has a range of household electricity tariff structures that depend on the region, supplier, and type of meter installed [52], and (b) the savings would depend on the program's compensation structure.

Further, Belgium at this stage does not have a national policy on smart metering, although smart meters are increasingly being deployed across the country [53][54]. A cost-benefit analysis of smart meters in Flanders suggested a positive business case for its rollout, yielding a net present value of €336 million over a 20-year discount period, even without taking the potential for peak demand reductions into account [55][6]. We thus do not assess the costs of implementation of a DR program here for two reasons: (1) smart meters are already being deployed for a range of broader objectives, and (2) there is already a positive business case for smart meter deployment without taking DR benefits into account. Our aim through this section is to consider these potential benefits from DR.

The numbers obtained above are broad estimates that rely on simplifying assumptions about the enrolment rates and household flexibility. As such, the actual financial values could be lower, and could further vary with the realization of other co-benefits. However, the estimates do indicate that there is an economic value to implementing a DR program, particularly if there are no significant additional costs. Furthermore, this value could increase with the range of appliances covered and the overall flexibility delivered. It may also benefit from enrolling all households in a time-based tariff structure, so that they are incentivized to deliver flexibility in the form of actual bill savings.

[6] However, other analyses in Flanders, Brussels, and Wallonia have been more inconclusive or negative, though methodological shortcomings have been noted in these analyses [56]

4. Conclusion and Policy Implications

Demand response programs can ease peaking generation requirements, balance the electricity markets, and help with the integration of renewable energies into the grid. Belgium in particular faces security of supply concerns due to potential outages at its ageing nuclear power plants, and is transitioning away from them in the short to medium term. This may augment the short-term risks to security of supply, and/or possibly increase the costs of electricity, as a greater share will come through imports.

Along with its supply side concerns, the country's winter peaks in electricity demand are significantly higher – by around 2 GW – than its summer peaks, and there is interest among policymakers in reducing these winter peaks in the short term. One way of addressing both these challenges is through DR programs, which are also promoted in the EU's Clean Energy for all Europeans package [57]. A previous DR trial in the Belgian region of Flanders has found that smart appliance programs could realize electricity consumption flexibility at a significant scale.

This paper conducted a discrete choice experiment – and estimated a panel mixed logit model – on 186 respondents in Flanders, to derive their willingness to accept a smart appliance-based DR program in the winter months. Such program could flatten winter peaks, thereby reducing the need for peaking generation and possibly balancing the market in case of further outages in the country's NPPs.

The paper found that respondents were most driven by how many days the program would be in effect, i.e., the fewer the number of days that they would have to shift appliance usage, the higher their utility. On the other hand, the hours per day were not significant. Together, these imply that the activity of shifting consumption was more onerous than the duration of the shifts, and suggest the presence of inertia or status quo effects. Respondents were also influenced by the compensation they would receive for the flexibility they offered. The appliances that would be controlled and the months that the program would run were not significant factors overall.

Also, younger and male respondents required a greater compensation to participate in a DR program for a given number of days per week than older and female respondents. Respondents who were more environmentally conscious and who owned, rather than rented, their homes were more willing to accept lower compensations for DR programs. Lastly, respondents with fewer privacy concerns were more likely to participate in these programs.

The results overall suggest that the implementation of a smart appliance program in the winter months – when carefully designed – can count on acceptance among the relatively young, well-educated segments, with higher levels of home-ownership, that were targeted in our research. This is not entirely in line with findings by Pepermans [19], who found that most households would be reluctant to adopt a smart meter, though the analysis did not consider the household benefits from DR. Sample simulations predict that up to 95% of the respondents in the sample could be willing to enroll in a DR program, running every day of the week, for a compensation of under €41 per household per annum. Because the sample is not fully representative of the population, the actual amounts required might be higher[7].

[7] Although respondents in general were supportive of a DR program, based on their answers to an optional feedback question, two respondents specifically mentioned that the compensation offered in the choice sets was not sufficient. Additionally, we expect that in some proportion of the cases where respondents opted for the "no-choice" option, they did so because of financial considerations

While the programs offered in the experiment would be more easily accepted among homeowners and environmentally-conscious people, and could thus be rolled out among these segments in a first phase, a general rollout among the wider population may require an explanation of first the financial, and then the environmental and energy benefits of the program. Specifically, the compensation listed in the choice set was not framed in terms of the potential electricity bill savings – these were not calculable since they would depend on participants' actual response and the compensation structures on offer. Making expected savings more evident might further increase the desirability of a DR program. Lastly, people's concerns with privacy and the sharing of information would need to be addressed, possibly through an explanation of the data collection process, and transparency regarding the uses to which it is put.

Different strategies should also be used among different population demographics to increase enrolment and response rates, and these should be based on further research and consultations, for instance on how to increase response among older male populations. Communication strategies could focus on women and populations more likely to be at home and/or responsible for operating the appliances.

To recapitulate, these recommendations are based on initial hypotheses that should be tested and validated by future research. One limitation of this study was that three of the five attributes included in the choice experiment focused on different dimensions of time, namely hours, days, and months. While these three are in no way substitutes for each other, future studies may consider replacing these by a greater number of non-time attributes. The role of heavier appliances such as refrigerators and heating systems may also be studied. A related point of note on structuring is that this study focused on a hypothetical smart appliance-based program, and the results are specific to the appliances covered. To obtain successful and complementary dynamic pricing structures, it may also be important to change the regulation of the electricity sector and increase the share of the variable component in the prices.

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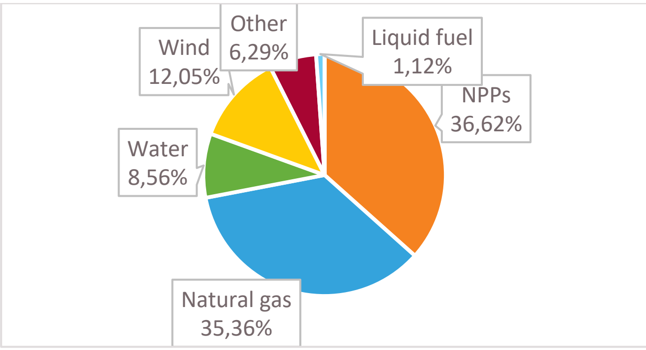
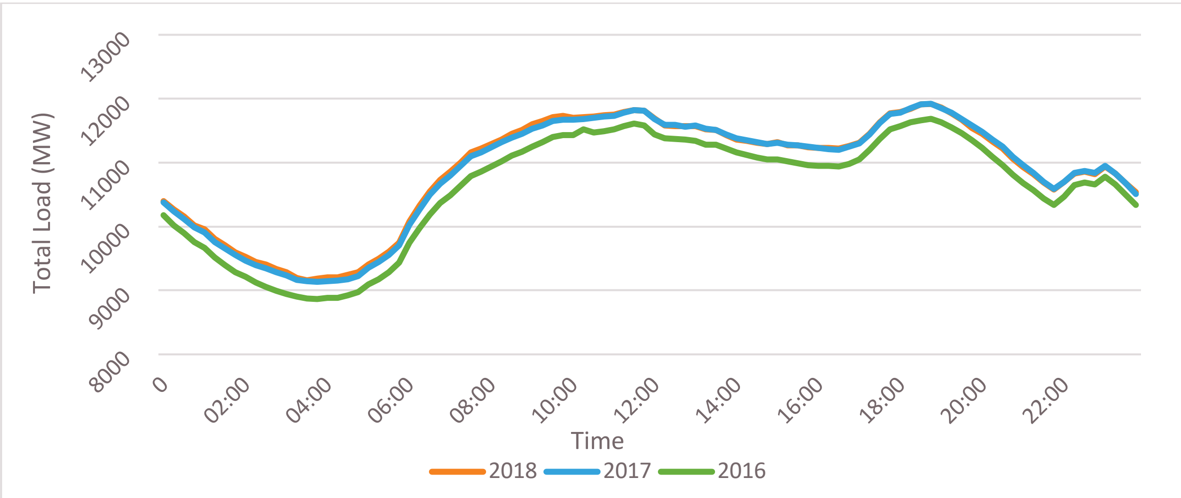
Tables and Figures

Figure 1: Shares of Installed Power in Belgium in 2019



Source: [26]

Figure 2: Average daily load curves, 1 January – 31 March



Source: [39]

Table 1: Main DCE - Attributes and Levels

Attribute	Level 1	Level 2	Level 3
Hours of day that appliances would be controlled	07.00-09.00 and 18.00-20.00	17.00-20.00	18.00-20.00
Days of week that program would run	All 7 days	All 5 weekdays	Any 2 weekdays
Months of the year that program would run	1 October – 1 April	1 November – 1 March	1 January – 1 March
Appliances that would be controlled when program is running	Washing machine, dishwasher, tumble dryer	Washing machine and dishwasher	Washing machine only
Compensation required to participate	€10	€18	€25

Figure 3: Sample Choice Set Used in Main DCE

	Option 1	Option 2
Hours per day	07h-09h and 18h-20h	18h-20h
Days per week	All 5 weekdays	All 7 days
Months per year	1 October - 1 April	1 November - 1 March
Appliances covered	Washing machine	Dishwasher
Reward (€)	25	10

○ Option 1 ○ Option 2 ○ Neither, prefer current situation

Table 2: Respondent Characteristics Relative to Belgian Population

Characteristic	Level	Percentage	Belgian Population
Age (Years)	[1] 18-29	47.3%	15-24: 11.3%
	[2] 30-44	18.3%	25-54: 40.1%
	[3] 45-59	21.5%	55-64: 14.2%
	[4] 60 or more	11.8%	65 or more: 18.6%
Gender	Male	53.8%	Male: 49.2%
	Female	44.1%	Female: 50.8%
Net Monthly Household Income	[1] <€2000	8.6%	Per capita: €3445
	[2] €2000-€3000	14.0%	
	[3] €3000-€4000	14.5%	
	[4] €4000-€5000	20.4%	
	[5] >€5000	14.5%	
Educational Degree Attained	[1] High school	21.0%	Upper secondary: 36%
	[2] Bachelor's	17.2%	Tertiary: 35%
	[3] Professional Bachelor's	10.8%	
	[4] Master's or higher	48.9%	
Housing Type	Apartment	19.4%	Apartments: 22%
	House	79.6%	Houses: 77%
Number of People in Household	1-2	31.2%	Average household: 2.34
	3-4	53.2%	
	5-6	14.5%	
Home Ownership	Rented	17.7%	
	Owned	80.1%	Owned: 72.7%
Tariff structure	Fixed tariff	34.9%	

	Variable (day/night) tariff	44.6%
Whether On a Green tariff	No	59.7%
	Yes	25.3%
Comfort with Sharing Additional Data with Electricity Provider (Privacy)	[1] Not at all comfortable	9.1%
	[2] Not comfortable	14.0%
	[3] Neutral	21.0%
	[4] Comfortable	24.7%
	[5] Very comfortable	29.6%
Environmental Activity Score[a]	1-4	43.0%
	5-8	48.4%
	9-11	6.5%
Comfort with New Technologies	[1] Not at all comfortable	0.5%
	[2] Not comfortable	1.1%
	[3] Neutral	13.4%
	[4] Comfortable	33.9%
	[5] Very comfortable	50%

[a] This score is a simple addition of the environmental actions that participants reportedly undertook from among 13 actions listed. However, not all actions were identical in scale or in the effort required.

Sources for population statistics: CIA Factbook [41], StatBel [42], OECD [43], Trading Economics [44], TekCarta [45], EC [46]

Table 4: Parameter Estimates and Goodness-of-Fit for Overall Model [a]

Effect	Posterior Mean	Posterior Std Dev	Subject Std Dev	LR χ^2 p-value
	Main Effects			
Days per week	-0.4209***	0.0840	0.4061	0.0000
Compensation	0.1868***	0.0969	0.0735	0.0005
No Choice Indicator	-0.3963***	1.7701	1.2447	0.0074
	Subject Effects			
Days per week * Age [2-1]	0.1607***	0.2087	0.1848	0.0009
Days per week * Age [3-2]	0.3052***	0.2943	0.1505	0.0009
Days per week * Age [4-3]	0.3446***	0.5726	0.1763	0.0009
Compensation * Environmental Score	0.0774 **	0.0190	0.0689	0.0238
Compensation * Home ownership	-0.1624***	0.0863	0.0806	0.0000
Compensation * Gender	0.1111***	0.0566	0.0772	0.0055
No Choice Indicator * Privacy [2-1]	-7.3217***	1.6434	0.9609	0.0000
No Choice Indicator * Privacy [3-2]	2.2319***	1.9781	0.9568	0.0000
No Choice Indicator * Privacy [4-3]	-2.6115***	1.9782	0.6023	0.0000
No Choice Indicator * Privacy [5-4]	-4.8206***	4.3257	0.9582	0.0000
No Choice Indicator * Age [2-1]	-0.1033***	1.6674	0.9153	0.0000
No Choice Indicator * Age [3-2]	0.8502***	3.4584	2.0105	0.0000
No Choice Indicator * Age [4-3]	-0.2431***	7.5138	2.7437	0.0000

Goodness of Fit Measure	Value
-2 * Average LL	944.5802

[a] $P < 0.01$: ***|| $P < 0.05$: **|| $P < 0.1$: *

Table 5: Policy Simulations based on Overall Model Results

Number of Days per Week Of DR	Compensation Required for 80% Enrolment	Compensation Required for 90% Enrolment	Compensation Required for 95% Enrolment
2	€3.7	€6.2	€10.2
3	€5.5	€9.3	€15.5
4	€7.3	€12.4	€21.1
5	€9.2	€15.5	€26.9
6	€11.1	€18.5	€33.3
7	€13.0	€21.6	€40.4

Figure 4: Enrolment Rates at Various Levels of Compensation