Power outages and bill savings : a choice experiment on residential demand response acceptability in Delhi

Power outages and bill savings:
A choice experiment on residential demand response acceptability in Delhi

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Abstract

This paper conducts a discrete choice experiment among 167 households in the Delhi region in India, to study the acceptability of demand response (DR) programs among upper-income households. Attributes include rate types, rate bands, reductions in power outages, and expected monthly savings. Results indicate a preference for time-of-use pricing over real-time pricing, and a preference for three rate slabs per day over two. Respondents prioritize reductions in power outages and minimizing potential expenses, reflecting the financial sensitivity and energy poverty relative to other countries. Respondents' ages and incomes further affect the value that they attach to reductions in power outages. The paper proposes various structures of DR programs that could achieve high predicted enrollment and concludes by estimating the potential benefits of implementing such programs. Overall, the analysis indicates that a DR program could be feasible in a developing country context, particularly if it is designed keeping in mind local socio-economic considerations. This may be supported through further confirmatory research.

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Highlights

- We conduct a choice experiment to design a demand response program in Delhi
- Results indicate a preference for time-of-use pricing over real-time pricing
- People care about the reductions in power outages and the potential expenses
- Ages and incomes affect the value that respondents attach to reducing power outages
- 90% of the sample can be predicted to enroll for savings of under $10 per month

Keywords: Demand response; Dynamic pricing; India; Discrete choice experiment; Asia; Residential electricity

Word Count: 7286

Abbreviations: Air conditioner (AC); Demand response (DR); Discrete choice experiment (DCE); Distribution system operator (DSO); Gigawatt (GW); Hierarchical Bayes (HB); Information and communication technology (ICT); Industrial and commercial (I&C); Kilowatt-hour (kWh); Log likelihood (LL); Megawatt-hour (MWh); Multinomial logit method (MNL); National capital region (NCR); Photovoltaic (PV); Real time pricing (RTP); Relative importance (RI); Renewable energy (RE); Time-of-use (ToU); Willingness to accept (WTA)

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1. Introduction

The global electricity sector is faced with two significant challenges. First, it is a significant contributor to climate change, with nearly 30% of total greenhouse gas emissions coming from electricity production [1]. Second, electricity consumption is increasing [2] which, coupled with the ongoing transition to renewable sources [3] that are variable in generation, presents a challenge for the security of energy supply.

Moderating electricity demand through demand response (DR) programs is a potential solution to these challenges. By shifting demand from peak to off-peak times and flattening demand curves through price signals, the automation of appliances, or direct control of electrical loads, DR programs can aid with the energy transition and grid integration of renewables [4], while increasing energy security [5] and reducing the overall costs of generation [6].

With significant response potentials [7], regions such as Europe and the US have introduced several policies and initiatives in support of demand response [8][9][10][11], and consequently DR programs are being increasingly tested in their residential sectors [12][13][14], aside from industrial and commercial sectors [15][16].

Literature on residential DR in these countries finds that results in many instances of DR implementation have been positive [17][18][19][20]. However, a growing body of research finds that varying consumer attitudes have led to a lack of responsiveness to such programs. Gyamfi et al [21] stated that a high fraction of households did not respond to price signals. Consumers were found to be less price-sensitive when they were more concerned about inconvenience or privacy [22][23][24]. Hall et al [25] identified that households want more information to understand the potential benefits of DR, while Brent et al [26] stated that knowledge about consumption can maximize the effectiveness of time-varying pricing.

In view of these heterogenous household preferences, Parrish et al [27] reaffirmed that findings can be complex and inconsistent, and that more research is needed on dynamic pricing. Gyamfi et al [21] suggested greater use of behavior-based approaches to address the challenges to achieving voluntary demand reductions, while Gambardella and Pahle [28] showed that customer heterogeneity affects the welfare gains from DR.

On the other hand, residential DR has not been greatly implemented in developing countries, possibly owing to the constraints on their electricity sectors, coupled with a lack of regular access to electricity by large proportions of the populations. A meta-analysis by Srivastava et al [29] found only two instances in developing countries and suggested that DR design should take local socioeconomic and political contexts into account.

There is a scope for such programs – developing countries are witnessing high levels of urbanization [30][31] and urbanization has been found to have the largest effect on non-renewable energy demand, compared with factors such as GDP or oil prices [32]. There is also an ongoing global debate on how developing countries can bypass traditional fossil fuel-intensive infrastructure [33][34][35] – India's coal production has grown at an average annual rate of 3.23% from 2009-2018 [36] – and move straight to renewables for their energy access and development objectives.

Among developing countries, the feasibility of DR has been most explored in China [37][38][39]. Energy management systems have been proposed for optimal DR scheduling in

South Africa [40], while scenario modeling has been used to guide industrial DR in Nigeria [41]. Surveys were used to assess customer willingness to participate in DR in Kuwait, which has a subsidized electricity market [42]. In India, the regulations and political economy of the electricity market have been studied for a DR introduction [43], and dynamic pricing has been studied specifically in the context of solar micro-grids [44]. However, to our knowledge, there are no concrete designs proposed for household DR implementation in any developing country.

This paper aims to address these two gaps, (1) the need for using more behavior-oriented approaches to design improved DR programs, and (2) the opportunity for considering DR in a developing country context. To do this, it uses a discrete choice experiment (DCE) to understand the acceptability of dynamic pricing-based DR programs in India, specifically in the National Capital Region (NCR) of Delhi, a region with conditions – high urbanization, high growth, ambitious renewable energy policies – suggested as ideal for DR implementation [29].

Existing research into DR programs has made limited use of the choice experiment approach. In developed countries, Ericson [45] estimated a discrete choice model using existing data from a residential critical peak pricing (CPP) experiment, to understand the bases on which consumers choose between tariffs. Pepermans [46] used a DCE to assess the extent to which consumers would use smart meters. Srivastava el al [47] estimated the acceptability of load control programs in Belgium, while Buryk et al [48] determined whether disclosing the environmental and system benefits of dynamic tariffs could increase customer adoption. Other studies [49][50][51][52] have also used choice models to understand preferences for other facets of electricity generation and provision. Existing choice experiment-based research has not greatly focused however on the actual structuring of DR programs. In this paper, we use this approach to obtain a valuation of the different attributes of DR programs specific to the local population, thereby helping better design such a program in the future.

The paper is set up as follows. Section 2 provides an overview of trends in the Indian electricity sector and consumer economy. Section 3 details the research method and design. Section 4 lists the results of the choice experiment study. Section 5 offers a discussion, with a cluster analysis of the sample, some policy implications of the results, and rough potential benefits of DR implementation. Section 6 concludes.

2. The Domestic Context

2.1 India's Electricity Situation

India's per capita electricity consumption is about 1100 kilowatt-hours (kWh) per year, or 8% of the US average [53]. This number conceals large disparities as, for instance, nearly 150 million people still had no access to regular electricity as of 2018 [54].

India's current generating capacity of 346 gigawatts (GW)[2] is expected to reach 600 GW by 2025 [55]. It is targeting a generation capacity of 175 GW from renewable sources by 2022 [56] – solar power contributed 40% to capacity additions in 2017 [57] – and it is likely to overachieve on this. However, power outages are frequent due to network problems – transmission and distribution losses are at 21.8%, and last-mile connectivity is inadequate [58].

[2] Of which 72 GW is from renewable energy sources [55]

The electricity sector has a system of cross-subsidies in its tariff structures, whereby the agricultural and residential sectors pay lower electricity tariffs that are subsidized by the industrial and commercial (I&C) sectors. The residential sector consumes 24% of the country's electricity [59] and has block tariffs that are determined by the individual states [60].

2.2 Trends in Delhi

The average monthly household electricity consumption in Delhi[3] is 181 kWh [62]. Though Delhi's bulk power rate is 60% more expensive than the national average, its retail tariffs are among the lowest [63]. Partly due to this, Delhi's peak electricity demand has grown by 64% between 2006 and 2018[4], and its 2018 peak of 7000 MW was more than the peaks for Mumbai and Chennai combined [65]. Despite this, the Delhi government offers subsidies that cost the government ₹16 billion ($230 million) in 2017[5] [66]. Analysis of these subsidies [66] has found them to be poorly designed: up to 96% of residents benefit from the subsidies – far more than the target lower income populations. The sector would thus benefit from a restructuring of these subsidies, or from broader tariff reform.

In Delhi, summer demand peaks tend to be twice as high as winter peaks [67]. During the summer months, the daily peaks typically occur around 3pm, when the day temperatures are highest, and then at night when people run their air conditioning units (ACs)[6] while sleeping. This trend in the planned and actual consumption of electricity is shown in Figure 1.

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[3] Delhi's core population is about 19 million, while the region under study has 26 million people [61]

[4] In early 2018, Delhi's electricity regulator cut tariffs across categories by up to 32%, though fixed charges were increased, further removing incentives to save on electricity consumption [64]

[5] One US dollar ($) is approximately 70 Indian rupees (₹)

[6] Unlike the centralized systems in more developed regions, each AC unit in India has its own individual thermostat controls and compressors

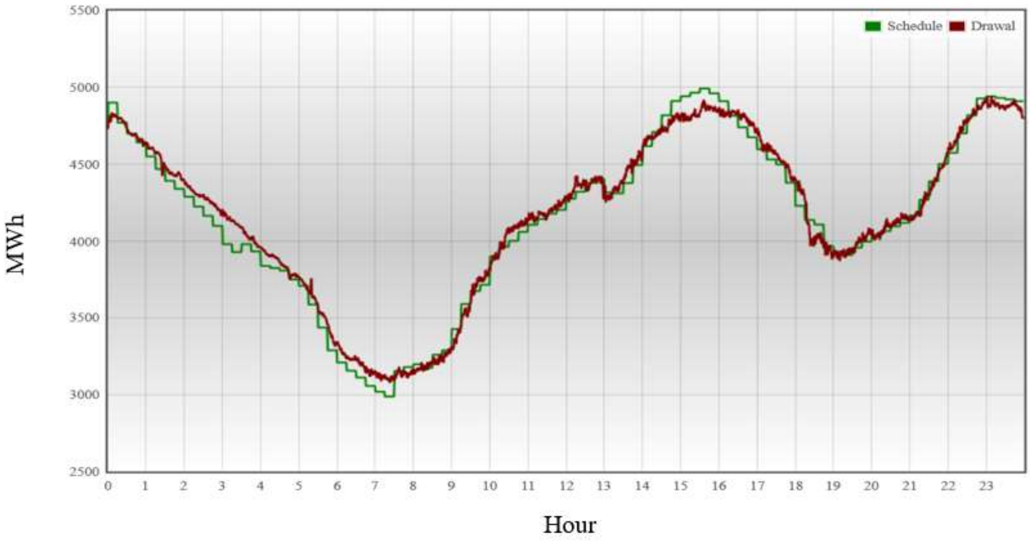


Figure 1: Planned (Schedule) and Actual (Drawal) Consumption in Delhi, June 21 2018

Source: Northern Regional Load Dispatch Center [68]

Against this, wholesale daytime electricity prices are cheaper than night prices, which are in turn cheaper than evening prices – Figure 2 shows the day-ahead wholesale pricing structure for Delhi. This creates a mismatch between pricing and consumption. However, electricity providers are penalized for over-drawing electricity from the spot markets above their stated expectations, and consumers are also to be compensated for unscheduled power outages [69].

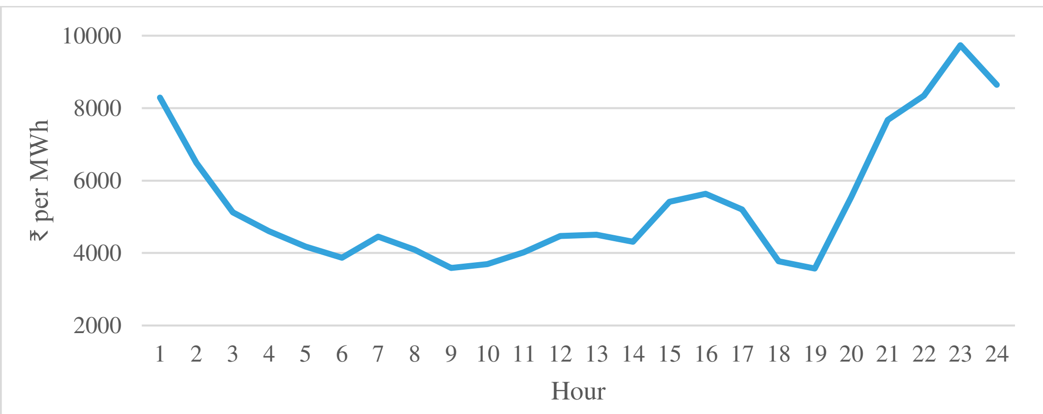


Figure 2: Average Day Ahead Prices for N2 Zone, June 20-22 2018

Source: Indian Energy Exchange [70]

2.3 Potential for Demand Response

With a high projected growth in electricity demand, and in light of access and grid reliability issues, there is an overall national focus on energy efficiency [71]. But demand response has not received significant attention yet, aside from limited initiatives in the I&C sectors, including in Delhi. One DR pilot among large consumers realized 17 MW in savings and is being more widely rolled out [72]. Another trial – using smart meters and load curtailment – found that customers can shed 10% of peak demand at the 75th percentile, although the results suggested that there is much more shed potential to explore [73].

To explore this shed potential, DR can be enabled through the ongoing shift in metering infrastructure that is accompanying the national government's smart grid and smart cities missions [74][75]. 130 million smart meters are expected to be installed across the country by 2021 [76] – Delhi alone is expected to have 1.6 million smart meters by 2025 [77], and its neighbors in the NCR are also rolling them out among customers [78]. DR implementation can be challenging because of the lower levels of electricity access, high rates of power theft and T&D losses, inefficient billing, and the poor financial health of the country's distribution system operators (DSOs). The Union Budget of 2021-22 announced an INR 3 trillion package to bail out DSOs by upgrading their technology and infrastructure, including rolling out smart metering and taking measures to reduce power theft [79].

The potential benefits of DR in India include reduced power outages, reduced electricity costs, offsetting the need to add capacity, and an ability to integrate electric vehicles and renewable energy sources [80].

Thus, the design of this study is informed by India's increasing electricity consumption and frequent power outages, its focus on renewables-based generation, the political sensitivities of tariff design and subsidies, and the rollout of DR-enabling infrastructure in line with a growing recognition of its potential.

3. Research Method and Design

3.1 Research Method: Discrete Choice Experiment

DCEs are a stated preference method – used to derive valuations where pricing cannot be determined by market mechanisms – that are based on the assumption that a choice between alternative options reflects the difference in utility derived from those options. A DCE design offers respondents several choice sets, with a number of alternatives within each choice set. Each alternative is described by various attributes and each attribute has a number of possible levels. The most statistically efficient design – that minimizes the confidence intervals around parameter estimates [81] – is determined using the D-efficiency[7]. The D-efficiency of a design is a function of the number of choice tasks, the number of attributes, and the number of levels per attribute [83].

Choice data from a DCE are analyzed using a logit model, which is consistent with random utility theory [84]. This theory assumes that individuals choose the alternative that maximizes

[7] D-efficiency is the geometric mean of the variances of the parameter estimates. The most efficient design is one that minimizes this mean [82]

their utility. It states that the utility U_k associated with an alternative k is a sum of its systematic and random components, as shown below.

$$U_k = V_k + \varepsilon_k = x'_k\beta + \varepsilon_k \qquad (1)$$

Where V is an indirect linear utility function, x_k are vectors describing the attributes of the alternatives, β are the preference parameters for changes in utility arising from changes in attribute levels, and ε_k is the stochastic term, which allows probabilistic statements about choice behavior.

The basic method used to analyze data generated by this type of experiment is the multinomial logit (MNL). Given a DCE design with J alternatives, the probability that a user, i, chooses alternative k in a standard MNL model is defined as:

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

MNL models however are restricted in that the preferences are assumed to be homogenous across responses, i.e. βs are same for everyone. Unlike MNL, which estimates only the mean preference effects of the attribute levels, the mixed logit accounts for heterogeneous preferences across respondents and correlation across repeated choices from the same respondent. It yields both a mean effect and a standard deviation of effects, i.e. it explicitly assumes that there is a distribution of preference weights across the sample [84]. Mixed logit probabilities are the integrals of standard logit probabilities over a density of parameters. Thus, in a mixed logit model, the choice probability for an alternative is given by

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

Where f(β) is a density function. To estimate the random parameters, we use the hierarchical Bayes (HB) technique under the assumption of normally distributed preference parameters without correlation between attributes. These estimated random parameters model the unobserved heterogeneity in the respondents' preferences [85]. If there is heterogeneity among individuals, HB can significantly improve a mixed logit model [86]. We rely on this mixed logit method for our model estimation.

The parameter estimates β are estimated through maximum likelihood methods. The log likelihood (LL) of a model can thus serve as an indicator of the goodness of fit and explanatory power of the model, where lower values of [-2 * LL] indicate a better model fit.

Lastly, 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.

$$WTA_A = \beta_A / (-\beta_M) \quad (4)$$

3.2 Research Design

We focused our choice experiment study on the Delhi NCR, since it is a large consumer of electricity with a higher percentage of higher-income – and potentially flexible – households [87]. This region has a total population of about 46 million people [88]. We limited our focus to Delhi and its neighboring towns of Gurgaon, Faridabad, Noida, and Ghaziabad, which cumulatively account for 26 million people. We expected that electricity savings from this region could be substantial enough to help meet future demand growth or support underserved areas. Additionally, by making the supply of energy more secure, DR can reduce the need for costly and polluting sources of captive power[8].

In determining the type of DR to use in our choice experiment, we noted that control-based programs may be more difficult for utilities to implement, given the infrastructure and resource requirements, and may have less acceptability in an energy-poor country like India. With this in mind, and considering the electricity sector's initial familiarity with time-based tariffs in the I&C space, we designed our experiment around real time pricing (RTP)[9] and ToU pricing, in which the peak and off-peak rates were designed considering average tariffs in the current upper blocks.

Given the higher summertime electricity consumption, we focused our survey and experiment on the months from April through September, when the day temperatures consistently exceed 35 degrees Celsius. We targeted upper middle-class households and above[10], namely those with a minimum monthly summer consumption of 300 kWh, which do not need to be subsidized[11]. To limit our sample to this demographic, at the outset of the survey we asked respondents to indicate their average summer monthly electricity billing amounts, and only accepted responses from those who owned at least 1 AC and whose monthly bills had been above ₹2500 ($36) at

[8] More than 10 million households in the country use battery storage UPS, and diesel generation sets across the country have a cumulative capacity of 90,000 MW [89][90]

[9] RTP rates are riskiest from the customer's viewpoint, but they will most likely be associated with the lowest average price [91]

[10] The top 20% of households earn 45% of India's income, and 87% of people living in metros belong to the top 2 income quintiles [92]

[11] This would address equity concerns and also mitigate the impacts of the skewed subsidy structure

least once. We expected that such households would be more willing to pay for an uninterrupted power supply. We further assumed that some of these households might be less price-elastic and could generate added revenues for the utilities, while others would be more price-elastic and could be the main source of peak shifts, as has been noted in previous studies [93].

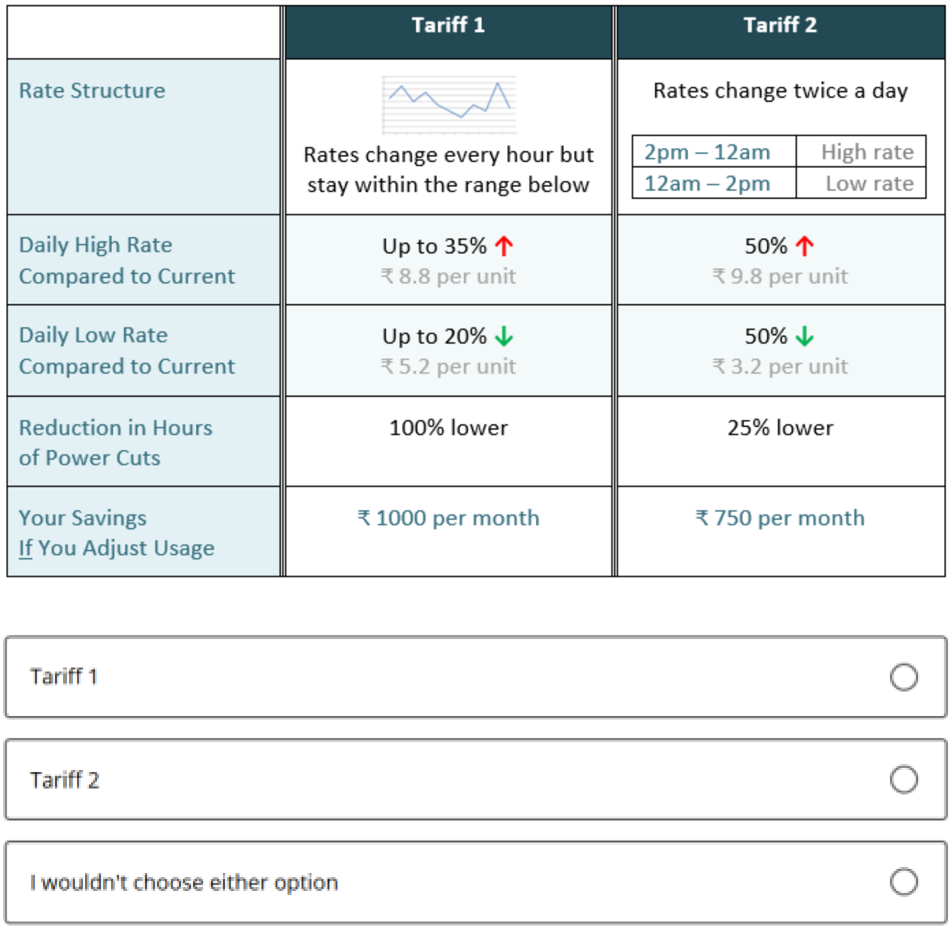
We used JMP 14 to create a Bayesian D-optimal design of 12 choice sets which we divided into two surveys – thus each respondent was presented with 6 choice sets of two alternatives. The designs are D-optimal because they guarantee that all parameters can be estimated with maximal precision. They are Bayesian because they include prior knowledge about the parameters in the form of a parameter distribution in the design process [94].

We assigned these prior values to our parameter distribution based on desk research and expert consultations, and allowed for a large amount of uncertainty around our expectations by specifying large prior variances. We then generated the designs in JMP 14. The attributes and levels used in the choice sets are captured in Table 1. In designing these, we also pre-tested the survey among 6 respondents and took their feedback into consideration.

Table 1: Choice Set Attributes and Levels

Attribute	**Levels**		
Rate structure	RTP hourly	ToU, three levels per day 18.00 – 00.00 High 00.00 – 07.00 Current 07.00 – 18.00 Low	ToU, two levels per day 14.00 – 00.00 High 00.00 – 14.00 Low
High rate	50% above current rate	35% above current rate	20% above current rate
Low rate	20% below current rate	35% below current rate	50% below current rate
Reduction in power outages	25% lower than present	50% lower than present	100% lower than present
Expected savings	₹400 per month	₹750 per month	₹1000 per month

A sample choice set is shown in Figure 3. The ordering of the 6 choice sets within each survey was randomized to reduce order effects. Besides the two alternative programs, each choice set also included a 'no-choice option' allowing respondents to opt out from any of the offered DR programs and stay with their current consumption pattern.



	Tariff 1	Tariff 2
Rate Structure	Rates change every hour but stay within the range below	Rates change twice a day 2pm – 12am: High rate 12am – 2pm: Low rate
Daily High Rate Compared to Current	Up to 35% ↑ ₹ 8.8 per unit	50% ↑ ₹ 9.8 per unit
Daily Low Rate Compared to Current	Up to 20% ↓ ₹ 5.2 per unit	50% ↓ ₹ 3.2 per unit
Reduction in Hours of Power Cuts	100% lower	25% lower
Your Savings If You Adjust Usage	₹ 1000 per month	₹ 750 per month

- Tariff 1
- Tariff 2
- I wouldn't choose either option

Figure 3: Sample Choice Set

The survey was designed in English; since most respondents in our target segments are comfortable with the language, this did not significantly increase the risk of selection bias[12].

[12] 12% of Indians were English speakers in 2011 and the overall English-speaking population was expected to quadruple in a decade. The percentage of English speakers increases significantly among urban regions and higher income populations [95]

The questionnaire consisted of 30 questions and was split into 4 parts. Part one listed questions about the respondent's electricity profile, such as appliance ownership, average power outages witnessed, availability of power backups, and average summertime monthly bills. Part two presented respondents with psychological profile questions, with scaled responses, to gauge their attitudes towards data privacy, convenience, technology, the environment, and their political affiliations. The order of these questions within part two was randomized. Part three included the choice exercise, and was randomly presented before or after part two, to further minimize order effects. In part three, we first listed the respondents' existing block tariff structures as a reminder, customized to the town in which they lived. Since the average rate in the highest blocks across all the 5 towns is roughly ₹6.50 ($0.09) per kWh, we then reiterated this figure as the marginal tariff across towns, for simplicity and comparability. We further explained the structure of the choice set exercise, as well as the potential for savings through DR[13]. We clarified that these savings could be realized if respondents chose to manually adjust their usage of electricity, and reiterated this through the language used in the choice set. Part four concluded with demographic questions. All questions were phrased in neutral language to minimize respondent manipulation, and we attempted to reduce potential hypothetical bias by explaining the real-life potential for such programs.

We conducted the survey through December 2018 and January 2019. Although these are winter months, we focused the questionnaire on summertime electricity characteristics to capture seasonal effects. To obtain these responses, the survey was disseminated online through Qualtrics. We used the following channels of distribution: (1) personal contacts as well as their contacts; (2) customers registered with a distribution utility – BSES – through one of its

[13] The average peak demand savings, across DR trials, has been about 10%, complementing energy efficiency initiatives [96], and when avoided generation costs and over-drawing penalties are passed through to customers, the savings can be significant [97]

employees; (3) Facebook groups for residents of Delhi, Gurgaon, and Noida; (4) local alumni chapters of two academic institutions in Delhi; and (5) other public posts on social media such as LinkedIn, Twitter, and Reddit. This may be viewed as a blend of convenience sampling and snowball sampling.

4. Results

4.1 Sample Statistics

Respondent data was anonymous and confidential. Although we do not have information about the non-response rates due to the nature of survey distribution, a total of 360 people filled out the survey. Of these, 278 were living in one of the five regions of the NCR under study. From these 278, 21 did not own any ACs, 32 had never had an electricity bill amount of above ₹2500, and 11 fell under both these categories. These 42 were thus ineligible for the choice set exercise. Of the remaining 236 eligible respondents, 167 (70.76%) completed the choice set exercise, clearly above the minimum sample size requirements for developing initial hypotheses [98]. The demographic details of these final 167 respondents are captured in Table 2 below.

Most respondents were between 25 and 55 years in age, and the sample was skewed towards male respondents, typically the main income earners and decisionmakers in a household[14]. Given the targeted nature of our survey, the sample was expectedly highly educated and fell under the higher income brackets, compared to the Delhi per capita of ₹27,400 ($390) per month [100].

[14] The total unemployment rate (female to male ratio) in India in 2018 was 1.56 [99]

Table 2: Respondent Demographics (N = 167)

Characteristic	Level	Respondents	Percentage
Age (in years)	[1] 18-24	11	7.01%
	[2] 25-39	74	47.13%
	[3] 40-54	35	22.29%
	[4] 55-64	20	12.74%
	[5] 65 and above	17	10.83%
Gender	[1] Female	43	27.74%
	[2] Male	112	72.26%
Net monthly household income	[1] <₹40,000	15	11.72%
	[2] ₹40,001-₹60,000	5	3.91%
	[3] ₹60,001-₹90,000	19	14.84%
	[4] ₹90,001-₹150,000	26	20.31%
	[5] ₹150,001-₹250,000	26	20.31%
	[6] >₹250,000	37	28.91%
Educational degree attained	[1] High school	5	3.36%
	[2] Bachelor’s	41	27.52%
	[3] Master’s or higher	103	69.13%
Car ownership	[1] None	13	8.23%
	[2] One car	71	44.94%
	[3] Two cars	53	33.54%
	[4] Three or more cars	21	13.29%
Employment of domestic help	[1] None	16	10.06%
	[2] At least 1 person part-time	86	54.09%
	[3] At least 1 person full-time	57	35.85%
Housing type	[1] Apartment	80	50.31%
	[2] Independent floor	33	20.75%
	[3] Independent house	46	28.93%
Number of people in household	[1] 1-2 people	39	24.68%
	[2] 3-4 people	74	46.84%
	[3] 5-6 people	33	20.89%
	[4] >6 people	12	7.59%
Home ownership	[1] Rent	44	27.67%
	[2] Own	112	70.44%
	[3] Other	3	1.89%

The electricity profiles of these respondents are captured in Table 3. Most respondents lived in Delhi or Gurgaon and owned three or more room ACs. 95% faced summertime power outages of under four hours per day, and 90% of them had at least one type of power backup system at home.

Table 3: Respondent Electricity Usage Profiles (N = 167)

Electricity Profile Question	Level	Respondents	Percentage
Part of National Capital Region (NCR)	[1] Delhi	76	45.51%
	[2] Gurgaon	65	38.92%
	[3] Noida	16	9.58%
	[4] Faridabad	2	1.20%
	[5] Ghaziabad	8	4.79%
Number of air conditioners at home	[1] One	19	11.38%
	[2] Two	36	21.56%
	[3] Three or more	112	67.07%
Monthly electricity bills amount in summer	[1] <₹2,500	16	9.76%
	[2] ₹2,500-₹5,000	55	33.54%
	[3] ₹5,000-₹7,500	37	22.56%
	[4] ₹7,500-₹10,000	28	17.07%
	[5] >₹10,000	28	17.07%
Other heavy appliances at home	[1] One	15	8.98%
	[2] Two	89	53.29%
	[3] Three	45	26.95%
	[4] Four	18	10.78%
Average daily power outages in summer	[1] 0-2 hours	127	76.97%
	[2] 2-4 hours	30	18.18%
	[3] 4-6 hours	6	3.64%
	[4] Above 6 hours	2	1.21%
Power backup system	[1] None	17	10.18%
	[2] Diesel-based	11	6.59%
	[3] UPS/Inverter	85	50.90%
	[4] Community backup	54	32.33%
Rooftop solar PV panels	[1] No	146	87.95%
	[2] Yes/Maybe	20	12.05%

The socio-psychological values of the respondents are captured in Table 4. Most were not very concerned about data privacy, suggesting that they may not be resistant to the introduction of smart meters. While 61% were very concerned about the environment, only 42% expressed a willingness to personally act on their concerns. A larger number of respondents seemed to be politically liberal than conservative, based on their news viewership, and most were comfortable with new technologies, and thus more likely to exhibit higher environmental concerns as found in previous studies [101].

Table 4: Respondent Values (N = 167)

Socio-Psychological Value	Level	Respondents	Percentage
Privacy 1 (On activities being recorded)	[1] Not at all comfortable	2	1.23%
	[2] Not very comfortable	27	16.56%
	[3] Fairly comfortable	61	37.42%
	[4] Very comfortable	73	44.79%
Privacy 2 (On personal information being stored)	[1] Not at all comfortable	2	1.22%
	[2] Not very comfortable	13	7.93%
	[3] Fairly comfortable	66	40.24%
	[4] Very comfortable	83	50.61%
Environment 1 (Importance of environment to respondent)	[1] Not at all important	6	3.68%
	[2] Not very important	2	1.23%
	[3] Neutral	11	6.75%
	[4] Somewhat important	45	27.61%
	[5] Very important	99	60.74%
Environment 2 (Willingness to spend on sustainable products)	[1] Completely disagree	6	3.68%
	[2] Somewhat disagree	13	7.97%
	[3] Neutral	11	6.75%
	[4] Somewhat agree	65	39.88%
	[5] Completely agree	68	41.72%
Convenience (Preference for shopping online)	[1] Completely disagree	15	9.20%
	[2] Somewhat disagree	26	15.95%
	[3] Neutral	43	26.38%
	[4] Somewhat agree	59	36.20%
	[5] Completely agree	20	12.27%
Political leaning (Preferred news channel)	[1] Right-leaning	41	25.15%
	[2] Left-leaning	70	42.94%
	[3] Others	52	31.90%
Technology 1 (On new technologies being better)	[1] Completely disagree	2	1.22%
	[2] Somewhat disagree	30	18.29%
	[3] Neutral	35	21.34%
	[4] Somewhat agree	75	45.73%
	[5] Completely agree	22	13.41%
Technology 2 (Ease of use of new technology)	[1] Completely disagree	0	0.00%
	[2] Somewhat disagree	23	14.02%
	[3] Neutral	27	16.46%
	[4] Somewhat agree	78	47.56%
	[5] Completely agree	36	21.95%

4.2 Logit Model Results

We first estimated the mixed logit model with main effects only, and the results are captured in Table 5. In this analysis, the base rate structure is the twice-a-day ToU, and the estimates for the other two rate structures are relative to this.

Table 5: Parameter Estimates and Goodness-of-Fit for Main Effects Model [a]

Effect	**Mixed logit**	
	Mean Estimate	*Std. Dev*
Rate structure [RTP]	-4.7249**	*1.6561*
Rate structure [ToU 3 times]	3.0103**	*1.3057*
High rate	-43.7282**	*9.4445*
Low rate	24.0235**	*6.8355*
Reduction in power outages	25.4045**	*4.2851*
Expected monthly savings	0.0196**	*0.0062*
No choice indicator	-71.8557	*18.1288*
Goodness of Fit Measure		Value
-2 * LL		134.5537
		Total Iterations: 15000

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

Expectedly, of the three rate structures, the real-time pricing had the lowest utility to respondents, since it would require the most effort to track. However, although we had expected the twice-a-day ToU to be the most preferred due to its simplicity, the three-times-a-day ToU yielded the highest utility across rate structures, reflecting the fact that it offered 6 hours of peak pricing, unlike the 10 hours in the twice-a-day ToU plan. Respondents attached the greatest importance to the upper price band, and to the reductions they could expect in power outages – these indicate the high value people attach to security of supply and price considerations.

Based on these mixed logit estimates, using Equation 4, we estimate the monthly savings that respondents would require – in rupees and as a percentage of the minimum qualifying bill amount of ₹2500 – for a change in each of the attributes, shown in Table 6, assuming that the rate changes and reductions in power outages are linear in utility[15].

Table 6: Monthly Savings Required for Changes

Attribute	Change Desired	Savings Required (% of ₹2500)
Rate Structure	ToU 3 times - RTP	₹ 393.14 (15.7%)
Rate Structure	ToU 3 times - ToU 2 times	₹ 65.85 (2.6%)
High Rate	10% increase	₹ 222.24 (8.9%)
Low Rate	10% reduction	-₹ 122.10 (-4.9%)
Reduction in Power Outages	10% reduction	-₹ 129.12 (-5.2%)

We then test for subject effects, and the results of this full model – capturing significant effects – are shown in Table 7.

Table 7: Parameter Estimates and Goodness-of-Fit for Overall Model [b]

Effect	Posterior Mean	Posterior Std. Dev	Subject Std. Dev
Main Effects			
Rate structure [RTP]	-9.5297**	4.7590	34.3279
Rate structure [ToU 3 times]	6.6491**	2.8787	23.7150
High rate	-69.4249**	18.1029	33.5181
Low rate	46.1991**	17.8895	85.9705
Reduction in power outages	38.6684**	10.4992	21.6869
Expected monthly savings	0.0642*	0.0344	0.0834
No choice indicator	-24.5196**	10.6798	6.1153
Subject Effects			
High rate * Monthly bills [2]	-31.6950	22.2196	56.5519
High rate * Monthly bills [3]	-57.7057**	22.2951	13.7876
High rate * Monthly bills [4]	-91.1971**	30.1354	7.0693
High rate * Monthly bills [5]	-23.1002	55.3610	4.3074
Reduction in power outages * Age [2]	21.8808	13.0266	10.9530
Reduction in power outages * Age [3]	-17.2219*	8.9144	11.6467
Reduction in power outages * Age [4]	-30.4321	23.0164	2.6994
Reduction in power outages * Age [5]	-29.3362**	14.3113	2.2346
Reduction in power outages * Income [2]	13.4181	18.2701	30.9496
Reduction in power outages * Income [3]	22.3316*	11.7106	24.7583

15 We tested for exponential utilities in the mixed logit model, but the goodness-of-fit and significance of parameter estimates was found to be lower in those cases

Reduction in power outages * Income [4]	25.7021**	11.6405	4.1048
Reduction in power outages * Income [5]	56.0497**	11.6642	5.9376
Reduction in power outages * Income [6]	63.2032**	23.2532	3.8995
Expected savings * Environment 1 [2]	0.1868**	0.0794	0.2356
Expected savings * Environment 1 [3]	0.1758**	0.0881	0.1382
Expected savings * Environment 1 [4]	0.0595*	0.0329	0.0610
Expected savings * Environment 1 [5]	0.0578	0.0426	0.0529
No choice indicator * Convenience [2]	-23.6463**	11.8685	5.3641
No choice indicator * Convenience [3]	-171.1601**	63.2396	116.6273
No choice indicator * Convenience [4]	33.5092**	14.3121	6.0846
No choice indicator * Convenience [5]	-491.1501*	253.4644	71.0172
No choice indicator * Home ownership [1]	34.1568**	15.9839	4.0730
No choice indicator * Home ownership [2]	28.3893**	11.3569	1.3049
Goodness of Fit Measure			**Value**
-2 * Average LL			69.1011
Total Iterations: 15000, Burn-in Iterations: 7500			

[b] P < 0.01: ***|| P < 0.05: **|| P < 0.1: *

5. Research Findings

5.1 Cluster Analysis of Preferences

Beyond the mixed logit model, we further study preference heterogeneity using a hierarchical clustering method to identify preference clusters, similar to the approaches previously with choice exercises [102][103]. Clustering sorts objects according to their similarity on desired dimensions and identifies groups that maximize within-group similarity and minimize between-group similarity [104]. This process is preferred over a single-step method like latent class logit because the former relies on a continuous distribution of preference heterogeneity – typically a more realistic scenario that allows for a parsimonious derivation of preference weights and their confidence intervals [102][105] – while the latter assumes a discrete distribution of preferences, in which heterogeneity is captured by membership in distinct classes [106].

For the dimensions, we use the subject-level coefficients for each attribute from the main-effects mixed logit model. Relying on the cubic clustering criterion values [107], we specify a four-cluster scheme, and identify the characteristics of the respondents within each cluster to examine differences between them. These characteristics are shown in Table 8, together with the averaged values of the attribute coefficients within each cluster. We do not pursue this exploratory analysis with confirmatory approaches such as regressions to determine predictors of cluster membership.

Table 8: Cluster Analysis Based on Preferences

	Sample N=167	**Cluster 1 N=34**	**Cluster 2 N=39**	**Cluster 3 N=27**	**Cluster 4 N=67**
Demographic					
Age (55 years or above)	22.15%	18.18%	25.64%	33.33%	18.18%
Gender (Female)	25.74%	18.18%	23.08%	25.93%	30.30%
Income (≥ ₹150,000)	37.72%	27.27%	53.84%	40.74%	31.82%
Car Ownership (≥ 3)	12.57%	18.18%	10.26%	14.81%	10.61%
Number of people (≥ 5)	26.95%	36.36%	25.64%	22.22%	25.76%
Home ownership	67.06%	69.69%	66.67%	70.37%	65.15%
Electricity Profile					
People in Delhi	45.51%	48.48%	43.59%	44.44%	43.94%
Number of ACs (≥ 3)	67.06%	63.63%	69.23%	74.07%	65.15%
Monthly bills (≥ ₹7500)	33.53%	36.36%	28.20%	40.74%	31.82%
Daily power outages (> 2 hrs.)	22.75%	24.24%	28.20%	25.93%	18.18%
Value					
Privacy 1 [Level 3,4]	80.24%	87.88%	76.92%	66.67%	83.33%
Environment 2 [Level 4,5]	79.64%	69.70%	87.18%	77.78%	80.30%
Convenience [Level 4,5]	47.31%	42.42%	46.15%	51.85%	46.97%
Technology 1 [Level 4,5]	58.08%	51.51%	69.23%	40.74%	63.64%
Utility Coefficients					
Rate Structure (RTP)	-4.50	-3.03	-1.30	-20.88	-0.43
Rate Structure (ToU 3)	3.13	-0.12	5.33	16.44	-1.97
High Rate	-48.90	-72.41	-21.23	-82.91	-39.59
Low Rate	23.41	-9.65	19.95	4.77	49.63
Reduction in Power Outages	26.84	28.07	74.28	5.16	7.08
Expected Savings	0.02	-0.07	-0.02	0.04	0.08

5.2 General Utility-Based Options

Yan et al [108], in a review of price-based DR, conclude that with smart metering technologies, pricing signals can be an effective instrument for peak demand reductions, reliability management, and emissions and cost reductions. With this in mind, we use our results to propose specific pricing signals for the Indian market. In doing so, we take two independent approaches to offering policy suggestions.

First, we use the main effects model to derive four DR structures that offer a high utility, drawing from the approach used by Byun and Lee [109]. To do this, we obtain the part-worth of each attribute k by multiplying its coefficient, β_k, with the range of attribute k. We note that the average sum of part-worths of the 24 D-efficient alternatives presented to respondents across choice sets is 21.29, and the standard distribution of their utility is 8.73.

Assuming a normal distribution, we set a target sum of part-worths at the 90% level (right-tailed p-value of 0.1) i.e. 32.47, and present four possible DR structures that approximately achieve this sum and that could feasibly be implemented among a general population, not taking into account the specific subject effects captured in the overall model. These four structures are presented in Table 9. For each proposed structure, we calculate the relative importance (RI) of each attribute, A – and its monetary value – within the structure, based on Equations 5 and 6.

$$RI_A = [\ |U_A| / \sum_{A=1}^{4} |U_A|\ ] * 100 \qquad (5)$$

$$Value_A = U_A \,/ \sum_{A=1}^{4} U_A * (Expected\ Savings) \tag{6}$$

Table 9: Potential DR Structures based on Main Effects

Attribute	Structure 1	Structure 2	Structure 3	Structure 4
Rate structure	ToU 2	ToU 3	ToU 3	RTP
RI	*5.84%*	*7.69%*	*6.52%*	*10.25%*
Value	*₹84.33*	*₹76.45*	*₹90.48*	*-₹160.45*
High rate	+15%	+20%	+30%	+20%
RI	*22.32%*	*22.34%*	*28.40%*	*18.98%*
Value	*-₹322.60*	*-₹222.10*	*-₹394.28*	*-₹296.99*
Low rate	-35%	-40%	-30%	-30%
RI	*28.61%*	*24.55%*	*15.60%*	*15.64%*
Value	*₹413.54*	*₹244.04*	*₹216.61*	*₹244.74*
Reduction in power	50%	70%	90%	100%
outages	*43.23%*	*45.42%*	*49.49%*	*55.13%*
RI	*₹624.73*	*₹451.62*	*₹687.19*	*₹862.70*
Value				
Expected monthly savings	₹800	₹550	₹600	₹650

5.3 Specific Enrollment-Based Options

Secondly, we develop six potential policy options – which are based on simulated sample enrollment rates – using the estimates from the full mixed logit model in Table 7, adopting the approach used by Bennett et al [110]. These options are complementary to the options proposed in Section 6.2, since we cannot predict their population enrollment rates. In these simulations, the predicted enrolment probability in a DR program k for respondent i ϵ {1…n} in the sample is estimated by the binomial logit characterization

$$P_{ik(Enroll)} = exp\ (\beta_x x_k + \beta_y y_{ik}) \,/\, [1 + exp\ (\beta x_k)] \tag{7}$$

Where y_{ik} are the user-specific indicator variables. Thus, the minimum payments c_k for the program k are the level of compensation at which the model predicts a targeted enrolment rate of R:

$$\Sigma^{N}_{i=1} F\,[P_{ik(Enroll)} \mid c_k] \,/\, N = R \qquad (8)$$

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

Table 10 shows the six policy options, with the reductions in power outages and the monthly savings that the sample respondents would require for predicted enrollment rates of 60%, 75%, and 90%.

Table 10: Policy Options for Various Levels of Sample Enrollment

Option	Rate Structure	High Rate	Low Rate	Reductions in Power Outages	Required Monthly Savings for Sample Enrollment of		
					60%	75%	90%
1	RTP	Up to 30% higher	Up to 20% lower	30%	₹140	₹240	₹380
2	RTP	Up to 40% higher	Up to 40% lower	80%	₹10	₹250	₹620
3	ToU 2 times	40% higher	50% lower	40%	₹150	₹320	₹510
4	ToU 2 times	20% higher	10% lower	20%	₹70	₹160	₹250
5	ToU 3 times	35% higher	20% lower	40%	₹130	₹270	₹460
6	ToU 3 times	50% higher	35% lower	60%	₹190	₹370	₹670

6. Policy Implications

6.1 Discussion of estimates

The overall model in Table 7 shows that the proportional utilities of the five attributes in relation to each other remain similar to the main effects model. However, the respondent profiles do affect the preferences among the various attribute levels.

The disutility from the high rate increases as respondents' monthly bill amounts increase, indicating a greater unwillingness to risk higher bill amounts. The high coefficients also indicate – in line with literature [48] – that respondents are very sensitive to prices and/or risk-averse, particularly if they're already paying a lot.

Younger respondents tend to derive a greater utility from reductions in power outages. 13 of the 17 respondents who did not have a power backup system, and 22 of the 38 who faced summertime power outages above 2 hours per day, fell in the first and second age categories, which may partly explain this trend. Yang et al. [111] had found, using survey data, that younger consumers are more likely to shift to ToU pricing programs than older ones, although their analysis was not related to energy security. Alongside security of supply issues, younger populations also tend to use more technological appliances [112] and may thus be more reliant on electricity for entertainment.

Higher levels of income also correlate to a greater utility from reductions in power outages. It is possible that richer populations are more willing to spend money on comfort. In line with this, 33 of the 63 respondents (52.4%) with a stated income of above ₹150,000 ($2140) per month valued convenience highly, compared with the sample average of 48.4%. This is in line with our initial expectations, that higher-income households would be more willing to pay for an uninterrupted power supply, and could generate added revenues for utilities. It is also in line with other literature [113][114] from developed countries, based on methods such as choice experiments and secondary survey data, which shows that higher incomes lead to greater values for comfort and convenience and correlates negatively with energy curtailment behavior.

The utility from expected monthly savings was increasing at a slowing rate with increases in the levels of environmental concern. However, the increase in utility was marginal, suggesting that people would not be willing to sacrifice too much in the interest of benefitting the environment. This was also seen from the relationship between the first and the second environmental questions, on the concern for the environment and the willingness to spend on more sustainable products, in Table 4. It runs against previous findings [46] from developed country contexts, although the potential environmental benefits of DR were not explained in our study.

People derived a lower utility from staying on the current plan if they owned their homes rather than renting them, and if they valued convenience more highly. This was somewhat counterintuitive, since staying with the status quo would inconvenience people less than shifting to a new tariff structure that requires a more active monitoring of rates.

We did not find significant effects for education rates, the presence of domestic help such as maids, power outages and backup systems, values towards privacy and technology. We expect that response bias, sample selection and size, and cultural differences may have played a role in these omissions. Further, to reduce cognitive burden and given the low market penetration rates, we did not include smart appliances in our study.

In discussing these results, we note that the Indian economy is growing rapidly, implying that more people will eventually move into the higher levels of income where expected price elasticity might be lower, as seen from the value of reduced power outages, yielding greater revenues for the utilities. At the same time, many more people may also enter the middle- to upper-middle income ranges, creating the potential for significantly higher peaks if consumption patterns are not meaningfully shifted.

6.2 Cluster Analysis of Preferences

In analyzing the clusters specified in Section 5.1, we see that Cluster 1 had more negative preference weights overall, and was more likely to select the no choice option i.e. reject the proposed DR structures and remain on the current tariff plan. Relatively, this cluster had the highest share of male respondents as well as the lowest income earners. The household size was the largest in this cluster, and AC ownership was lower. Respondents had the lowest privacy concerns, lowest scores on convenience, and lowest willingness to spend more for environmentally-friendly products.

Cluster 2 had a strong preference for reductions in power outages and in general experienced less disutility from the higher peak rates. This cluster had the highest incomes, though car ownership was lower. Respondents in this cluster were most willing to spend more on environmentally-friendly products, and were very comfortable with new technologies.

Cluster 3 exhibited very strong preferences for the rate structures and higher peak rates, and comparatively weak preferences for reductions in power outages. This cluster had more older respondents, smaller household sizes, and the highest rates of home and car ownership. Respondents also owned more ACs and had larger monthly electricity bills. They had stronger privacy concerns, and greater preferences for convenience, but were least comfortable with new technologies.

Lastly, cluster 4 – with the largest population – had comparatively strong preferences for the lower off-peak rates and for the expected savings, and were relatively indifferent to the rate structures. This cluster included more younger respondents, as well as more female respondents. They had lower incomes and fewer cars, and the lowest rates of home ownership. Respondents in this cluster also faced the fewest power outages.

Though we note that certain characteristics, such as home ownership rates, were not significantly different across the clusters, these clusters indicate that even among higher income households in the NCR, different groups within the sample have different concerns, likely shaped by their different characteristics. Further, we acknowledge that this sample may not represent the middle- and upper income residents across India; however, it offers initial insights into the large populations of the NCR, and can be used as a basis for further studying similar urban regions in India. These varying concerns will have different effects on future DR adoption.

6.3 General Utility-Based Options

Of the four DR structures in Table 9, the most preferred rate structure, three-times-a-day ToU, could potentially have a greater variance in the upper and lower rates, and would require the lowest monthly savings as long as it achieves a moderate reduction in power outages. RTP structures could achieve the same utility, so long as the rates do not vary greatly and they realize significant reductions in power outages. As we expect a twice-a-day ToU structure to realize a lesser reduction in power outages, their acceptance based on this utility approach would require higher monthly bill savings.

6.4 Specific Enrollment-Based Options

Among the six policy options in Table 10 above, the cheapest option is option 4, where the flattest rate structure compensates for a limited reduction in power outages, enabling a 90% sample enrollment for savings of just ₹250 ($3.60) per month[16]. However, all six options predict a 90% sample enrollment for savings of under ₹700 ($10) per month, which is under 30% of the minimum summer monthly bill amounts of the participating households.

Figure 4 additionally shows the predicted enrollment rates for these policy options at various levels of expected monthly savings. Options 2 and 4 have the highest predicted enrollment when the expected monthly savings are negligible. In the middle brackets of expected savings, around ₹100-₹400 ($1.40-$5.70) per month, options 1 and 4 – offering both the lowest peak rates and least reductions in power outages – would enroll the greatest shares of the sample. Options 3 and 5 would witness stable increases in enrollment. Option 1, offering RTP with

[16] We note that what is cheapest for customers may not be the most valuable to the power system, and any DR program implementation will involve trade-offs between savings for customers and the costs to the utilities

higher off-peak rates and fewer reductions in power outages, is the least attractive in the absence of significant savings.

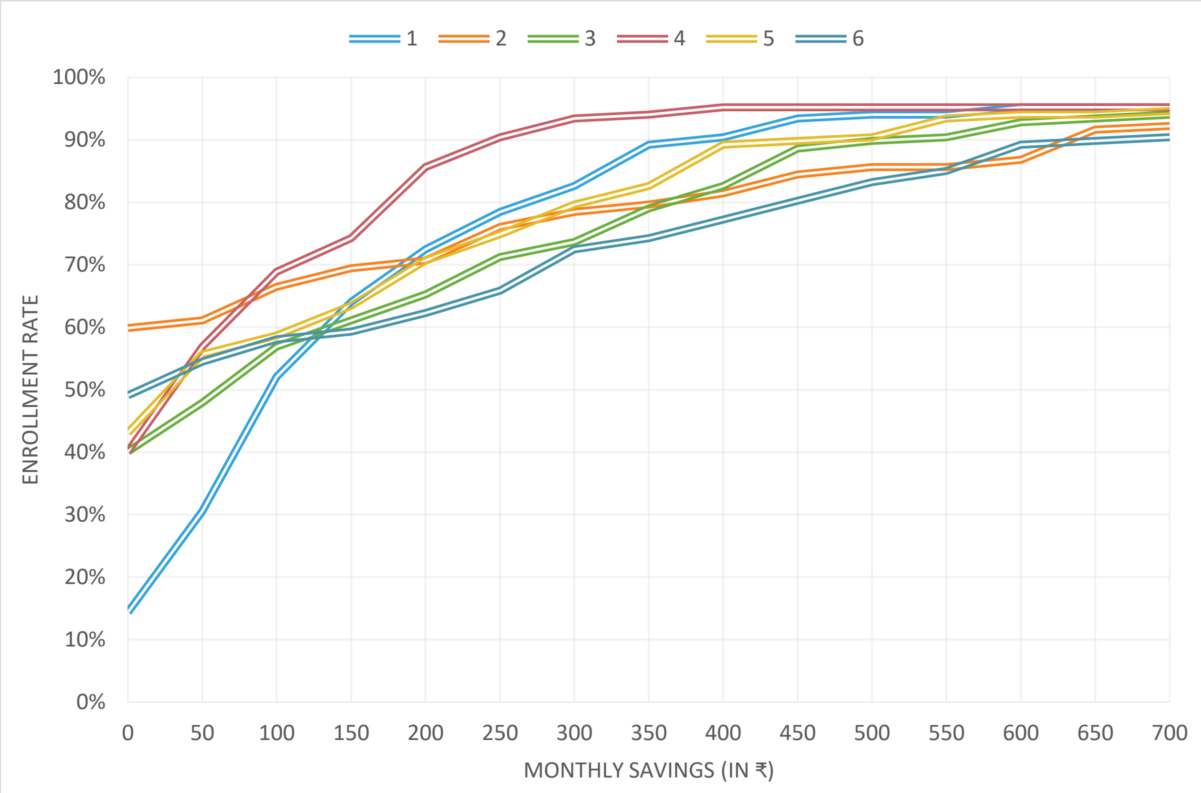


Figure 4: Sample Enrollment Rates for Policy Options

We note that the predicted enrollment rates would be dependent not just on the levels of expected savings, but also on the DR structures being able to offer these predicted reductions in power outages.

6.5 Economic Value of Demand Response Implementation

We explore the economic value of shifts in consumption once a dynamic pricing program is introduced. We however do not look at the costs of implementing such a program. We choose the rates structures outlined in Option 5 above, since it falls in the middle of the other options in terms of enrollment rates, as seen in Figure 4.

We consider the effects on Delhi alone, and do not include the other NCR regions in this study. There were about 3.7 million households in Delhi in 2009-10 [115]; we expect that with urbanization, population growth rates, and nuclearization of families that there are currently around 4 million households.

We then assume that the DR program is applied to the richest 20% of Delhi's population, similar to the set-up in this choice experiment, which comes to about 800,000 households of the 3.7 million. We expect that these 20% of households are responsible for about 45% of the city's residential electricity consumption, in line with the shares of income mentioned in Section 3.2.

In Option 5, the difference between the peak (35% higher, or ₹8.8) and off-peak (20% lower, or ₹5.2) rates is ₹3.6 per kWh. Given that each room AC uses an average of 1.8 kW [116][117], then for each hour that an AC's usage is shifted from peak to off-peak hours, the marginal impact on savings would come to (1) ₹3.6 x 1.8 = ₹6.48 ($0.09), relative to consuming at peak hours, and (2) ₹1.3 x 1.8 = ₹2.34 ($0.03), relative to the current average tariff of ₹6.5. Thus, if a household shifts consumption of 1 AC for two hours each evening, the monthly savings for a household consuming 407 kWh come to about (1) ₹390 ($5.60), compared to consuming at peak hours (10.47% of the current average bill), or (2) ₹140 ($2.00), compared to consuming under the current tariff structure (3.76% of the current average bill). This looks at only the marginal impacts of shifting AC usage and does not consider other impacts of shifts in the overall consumption profile. These savings can become more significant if further flexibility is induced in other ACs, water heaters, washing machines, and other appliances.

Further, the residential sector accounts for 44% of Delhi's total electricity demand [118]. For simplicity – and given a lack of available data – we assume it constitutes 50%, or 3500 MW, of the 7000 MW peak. If the top 20% of households are responsible for 45% of total residential consumption, in line with India's income trends [92], and 50% of the shares at peak hours for simplicity, then they would account for 1750 MW of the peak demand. Shifts of even 10%, which have been observed in DR programs in other countries [96][119], could thus lead to reductions in peak demand of up to 175 MW.

7. Conclusion

This paper used a discrete choice experiment to test the acceptability of implementing a dynamic pricing-based demand response program in the residential sector in India.

India is a developing economy with a large low-income population, many still lacking regular access to electricity. Additionally, it is experiencing high economic growth, high growth in consumption, and consequently large increases in greenhouse gas emissions. This creates the incentive for using DR to improve the security of supply, particularly with India's ambitious renewables targets. The opportunity for implementing such DR programs comes from India's smart grid ambitions and its smart metering targets.

The analysis focused on a part of the national capital region of Delhi. This was due to considerations of homogeneity – each state in India has its own electricity tariff structure – and socio-cultural comparability. With a population of 26 million people, an implementation even in this region alone can yield sizeable effects, particularly as Delhi has the highest per capita energy consumption rates in the country. The expectation is that any peak reductions can be used to improve electricity access to underserved populations, while any additional revenues to utilities can be used to improve the provision of electricity services and the grid infrastructure.

The target population was higher income households who had a summertime monthly bill above ₹2500 and who owned at least one room AC. We obtained 167 usable responses for our analysis, where each respondent was presented with six choice sets of two alternatives. Each alternative was comprised of five attributes with three possible levels.

The results showed that respondents preferred ToU pricing to RTP structures, because they are easier to track. Within ToU structures, they preferred the three-rate structure to the two-rate structure, perhaps because the former offered a fewer number of hours of peak pricing than the latter. In general, however, respondents attached a lower utility to the different types of rate structures than to the remaining attributes.

Although the off-peak rates were not as important, respondents exhibited a strong preference for lower peak time rates, particularly if their monthly electricity bills were already high. This indicated a greater aversion to risk and a greater unwillingness for potentially further inflating existing bill amounts.

Respondents attached a high value to reductions in power outages, indicative of the extent of supply-side problems. Younger and higher income respondents in particular attached a higher utility to such reductions, owing to a mix of greater technological appliance usage and lower ownership of power backup systems among the former, and a greater value of convenience among the latter group. Although respondents who were more concerned about the environment attached a lower utility to the required monthly savings, this amount was not substantial and indicated that environmental concern does not necessarily translate to action. This was in line with the risk of hypothetical bias that is faced by choice experiments, and also suggests that environmental issues are a secondary consideration in energy consumption. A cluster analysis demonstrated that respondents that exhibit similar preferences also share similar characteristics that are distinct from those of respondents in other clusters.

Based on results, the paper then presented a number of potential DR structures that could be implemented, and that were designed to either yield a high general utility or achieve a high predicted enrollment among the sample. Lastly, it offered a rough estimate of the potential benefits – to households and utilities – of implementing one of these structures.

Overall, the analysis indicates that a dynamic pricing-based DR program could be feasible in such a developing country context, particularly when it is designed for higher income households and addresses local electricity sector considerations. While framing it as an environmental solution may help to some extent, the key concerns for the local population are expected savings and reductions in power outages. Thus, any DR program would have to clearly be able to address people's price sensitivities and security of supply concerns.

We acknowledge that we did not offer smart appliances and smart meters in our hypothetical choice exercise, although their availability may also affect the desirability of such programs, and the potential impacts on power outages were hypothetical.

Aside from the risk of hypothetical bias, discrete choice experiments should also be interpreted differently from actual trials, because the short run and long run price elasticities are measurably different due to behavioral learning over time, and due to stock changes (e.g. buying smart or more efficient appliances) [120][121]. Price-based DR programs also run the risk that they may attract consumers who benefit without responding to the price, simply because they already have a favorable consumption pattern [46], although this has not been found to be a significant factor in previous analyses [45].

However, we believe that the potential benefits of choice experiments, particularly as indicators of market feasibility, outweigh their limitations. Although the sample size was limited, the research offers indicative results that may be validated through further research. Future studies looking at the Indian context may consider applying similar methods to other cities, in order to consider the design requirements for a national roll-out, and may look at the techno-economic feasibility and challenges of actually implementing such programs.

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