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Data Science for Energy
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Cool for the Summer: Behavioral Modeling and HVAC Control for Demand Response

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1.0 Abstract

Peak electricity demand events are expensive to consumers, encourage the continued operation of polluting fossil fuel generators, and can cause blackouts. Demand response (DR) is widely recognized as a low cost and effective way to reduce peak demand. Our proposal drafts an agreement with residential consumers for a utility or aggregator to manage their HVAC systems within a certain temperature range for select days per year for demand response. This study conducts a stated preference survey and develops a discrete choice model to evaluate consumers' willingness-to-participate in the program under varying conditions of control and payment. Temperature set point is used as a controllable input into a building thermal system model to estimate demand reduction under different temperature setpoint changes and hours of the day. Comparing scenarios for control parameters, reward payment, and resulting load reduction, we make recommendations on the optimal program design. The study is contextualized to Sacramento and peak demand days that occurred on the California grid in recent years.

2.0 Introduction

2.1 Motivation & Background

2.1.1 Introduction to Demand Response Programs

As climate change continues to foster rising temperatures and power consumption and renewable energy production increases, grid fluctuations are also becoming more extreme (Wang, Jingjie, et al). These extreme events can be both expensive to users as well as the environment in terms of emissions. As such, there is a heightened demand to develop an effective methodology to control energy consumption based on grid demand. The idea of demand response, which focuses on changing customer electric consumption patterns based on electricity prices or incentive payments, is becoming a popular focus of academic research and policy action in order to address these challenges. In 2021 the California Public Utilities Commission (CPUC) announced the "Market Access Program," authorizing $150 million over two years to fund projects that reduce peak demand. This initiative seeks to simplify and streamline the rules of measurement and verification for aggregators to get paid through a demand "FLEXmarket" (Market Access Program, CPUC).

2.1.2 Associated Challenges

Demand response is directly dependent on complex human decisions, thus it is essential to incorporate behavioral modeling when predicting, evaluating and even optimizing the impact of such programs. In terms of managing HVAC systems, there is a wide range of individual comfort levels regarding temperature. The optimized temperature levels during periods of control may not fit the needs or preferences of all individuals, posing a challenge in the actual determination of these temperature ranges. Therefore, behavioral modeling can provide information on whether certain demographic and household characteristics are associated with higher willingness to participate in the program and whether the value of comfort differs among different groups of people. This is important information for the demand response program to be an effective tool for managing energy demand and promoting the integration of renewable energy sources.

2.1.3 Research Team Experience

This team is well positioned to study this topic, with all team members having coding backgrounds in both Python and MATLAB. In addition to taking CE295, the majority of the team is also enrolled in CE264, Behavioral Modeling for Engineering, Planning and Policy Analysis, providing us with the tools to successfully integrate behavioral modeling into the study. Jackson has multiple years of work experience within the energy field including specific work on load flexibility. Coby was in the electrical engineering department in his undergraduate program, bringing insight into power systems to the team.

2.1.4 Inclusion of Additional Research

The proposed topic integrates very well with CE264, as the adoption of such a system requires an understanding of human preferences and choices regarding personal energy usage patterns and responsiveness to an incentive program. Specifically, while we plan to develop a technical model for HVAC control, the real world effectiveness of this model relies on human adoption of the program built upon the model.

2.2 Relevant Literature

Key references for this research project include studies from both academic and scientific journals, which can be found in References. Those that are particularly relevant to the focus of this project are summarized below.

Dyson et al.'s (2014) study on demand response potential of residential air conditioning showed promising results that could also indicate application to solar energy integration. Utilizing linear regression and unsupervised classification, they discovered that the range of potential load impacts in Northern California, between 270-360 MW, can be delivered over a 1-hour duration with a 4°F temperature setpoint change. Further analysis also indicated high correlation with evening decline in solar production, confirming the potential of demand response to act as reserves during these periods.

Wang et al. (2021) performed a similar study analyzing air-conditioning user's demand response behavior in which they developed 3 models that are of interest to our study. This includes the following: a cooling load demand model that considers comfort temperature, a user response model under an electricity mechanism (based on the discrete choice model), and a user decision optimization model that minimizes cooling cost and considers optimal cooling comfort. The user solution process outlined in this paper could provide comprehensive user response decision information that could be valuable to the construction of our proposed demand response model and analysis of the acceptability of our proposed program. However, our demand response program design differs in the use of a monthly payment for reward, rather than dynamic pricing and user response (i.e. non-automated) control.

Similarly to above, Shi et al. (2020) conduct a study to estimate the profile of demand response programs with dynamic modeling of HVAC systems and hot water heaters. Importantly, they determine a closed form relationship that relates the temperature setpoint change to the load reduction over the course of 45 minutes of control, as well as average thermal parameters for residences that we can adopt for our study. They conducted a survey of 1575 customers in New York and Texas to model the potential for peak load reduction in each geography. Their survey simply asked respondents the minimum monthly reward payment they would require to participate in a program for 45 minutes of control. Our work extends these results with a more robust discrete choice model that can be used to estimate market share under different parameters for control (e.g. time, temperature setpoint) and reward.

2.3 Focus of this study

The focus of this study is to explore optimal design of a novel demand response program in which participants are paid a reward in exchange for allowing an aggregator or utility to control the participants thermostat on select days per year. The study conducts a discrete choice behavioral experiment to model consumers willingness-to-participate in the program under different parameters of control.

3.0 Technical Description

3.1 Survey Design

The first step in our research was to collect preference data for our proposed Demand Response program through a Stated Preference (SP) survey. This type of survey allows us to understand human behavior and preferences under hypothetical scenarios, which in the context of this project, is the DR program itself. The survey began with an introduction to the DR program, and presented respondents with 5 randomized DR programs, an example of which can be seen in Figure 1. Some attributes for the proposed program include monetary rewards, temperature change and control timeframe and the respondent chooses either "Yes" or "No" to state whether they would enroll in this particular program. The survey also included additional questions to collect relevant information that might be influential in their decision to enroll or not, including demographic characteristics of the respondents. The survey was deployed through Qualtrics and the survey link was shared with Berkeley students, faculty, friends and family members.

This survey is designed to assess residential energy consumers' willingness to participate in a Demand Response (DR) program that can benefit the electricity grid and the environment. Peak demand events occur in California during summer heat waves, particularly when production from solar energy is rolling off and electricity demand for cooling across the state is high. By setting back your thermostat by just a few degrees, you can have a big impact on reducing this demand peak. This helps avoid blackouts, reduces GHG emissions, and facilitates the grid's transition to clean energy.

Suppose your utility offers a DR program for the 4 summer months of June, July, August, and September. They will provide a free automatic controller installed in your thermostat, and during a DR Event you will receive a text the day of the event that will let you know the hours during which your thermostat settings will be adjusted. This will likely occur in the afternoon hours during heat waves. If you choose to override the thermostat, you will forego the incentive payment for that day. The incentive will be paid out through your utility bill at the end of the month. For the purpose of this survey, please assume you have the decision making authority for your household and your household has central air conditioning.

The survey will begin by presenting a variety of enrollment scenarios followed by a short series of questions about personal demographics and living situations.

Given the following program scenario, would you choose to enroll in the Demand Response program?

	Choice 1
Utility Controlled Days Per Month	3
Hours Controlled by Utility	5
Relative Temperature After Adjustment by Utility	Slightly Warm (+2.5 F / +1.4 C)
Expected Reward Per Month ($)	70
Percent reduction in risk of blackout	90%
Percent reduction in CO2 emissions	5%

Figure 1. DR program description (left) and example choice set (right).

The survey is available here.

3.2 Discrete Choice Model Description

Using the survey results, we next constructed a binary logit model.. This model consists of variables measuring attributes and characteristics of the choice and the survey-taker, respectively. The choice set includes participation and non-participation in the program, denoted as C_n={$opt\ in, opt\ out$}. The utilities can be divided into the systematic components and the random components.

The systematic component is a function of the characteristics of the decision-maker, *n*, and the attributes of the program, and specified as follows:

$$V_{opt\ out,n} = 0$$

$$V_{opt\ in,n} = \beta_1 X_{Monthly\ Incentive} + \beta_2\ X_{Days\ \times Hours\ \times \Delta T} + \beta_3 X_{\Delta T, 80-90°F} + \beta_4 X_{\Delta T, 90-100°F}$$

$$+\beta_5 X_{Democrat} + \beta_6 X_{\%\ CO2\ Reduction} + \beta_7 X_{AC\ Window\ Unit(s)}$$

Under the assumption that the random component is Extreme Value distributed, and the choice probability for opt in is:

$$P_n(opt\ in) = \frac{e^{\mu V_{opt\ in,n}}}{e^{\mu V_{opt\ in,n}} + e^{\mu V_{opt\ out,n}}}$$

A description of the parameters included in the model can be seen in Table 1 below.

Table 1. Model Parameter Descriptions

Parameter	Description
β_1	Monthly incentive
β_2	Days x Hours x Temperature Change
β_3	Temperature Change, if located in 80-90 °F
β_4	Temperature Change, if located in 90-100 °F
β_5	Democratic Party (1 if Democratic, 0 otherwise)
β_6	CO2 % Reduction
β_7	Owns AC window unit(s) (1 if yes, 0 otherwise)

3.3 Aggregated HVAC Model

For this portion of the project we adopt the following equations and parameters from Shi, Qinxin, et al. (2022). The discrete form of a simple one-order thermal transfer model of fixed-frequency HVAC can be written as:

$$\theta_a(t+\Delta t) = \theta_a(t) + \frac{\Delta t}{C_A}\left[\frac{\theta_{a,out}(t) - \theta_a(t)}{R_A} - S_A(t)Q_A\right]$$

The parameters are specified in Table 1 and $S_A(t)$ is the ON/OFF function governed by a thermostatic switching law with the temperature deadband:

$$S_A(t) = \begin{cases} 0, & \text{if } S_A(t-\Delta t) = 1 \;\&\; T(t) \le T_{min} \\ 1, & \text{if } S_A(t-\Delta t) = 0 \;\&\; T(t) \ge T_{max} \\ S_A(t-\Delta t), & \text{otherwise} \end{cases}$$

$\theta_{a,min}$ and $\theta_{a,max}$ are the upper and lower limits of the deadband and defined as:

$$\theta_{a,min} = \theta_{a,s} - 0.5\theta_{a,db}$$
$$\theta_{a,max} = \theta_{a,s} + 0.5\theta_{a,db}$$

We model the power consumption for a single house using Python scipy.signal library for every minute of the day for 24 hours. We take the temperature context to be the city of Sacramento, CA during a summer heat wave day. To enhance the accuracy and usability of the result, more presentative parameters for the building characteristics of the local context should be used. We adopt the parameters from Shi, Qinxin, et al. (2022), but in practice a utility or program operator could try to collect this information from their customer base as part of the survey process.

Table 2: Building thermal model and HVAC parameters.

Parameter	Description	Typical values
A_r	House area	$150\,m^2$
R_A	Thermal resistance of target house	$100/A_r$ °C/kW
C_A	Thermal capacitance of target house	$0.015A_r$ kWh/°C
Q_A	Heat transfer rate (positive for colling, negative for heating)	$0.14A_r$ kW
$\theta_{a,s}$	Temperature setting of HVAC	-
$\theta_{a,db}$	Thermostat deadband of HVAC	2.4 °C
η	Cooling efficiency	2.5
$\theta_{a,out}$	Outside air temperature	-

Due to the small capacity and large quantity of the individual HVAC systems, aggregation is critical to integrate the HVAC systems into power system operations. In our analysis, we simulate 500 homes with uniform random distributions of House Area, Thermal Resistance, and Heat Capacitance. Based on the known outside air temperature profile of the day, the ON/OFF function $S_A(t)$ of each house can be simulated with the above equations, and the aggregate electricity demand profile ($P_A(t)$) can be obtained by:

$$P_A(t) = \frac{1}{\eta}\sum_{i=1}^{N_F} S^i{}_A(t) Q^i{}_A$$

Inputs to the aggregated simulation are the outdoor temperature, baseline setpoint temperature, temperature setpoint change, and beginning and end hours of the demand response event. The output is the aggregated load profile before and after the demand response event. Locational Marginal Price (LMP) of electricity in Sacramento on September 6th, 2022 is obtained from CAISO OASIS database[1], which is used to calculate average bulk electricity cost savings per household for the specified controls and day. The results are extrapolated to the year, but enhanced modeling should incorporate more differentiated demand response days in terms of temperature profile and electricity cost.

3.4 HVAC Optimal Control

As part of our exploration with the methods of CE 295, we decided to explore optimal control of HVAC systems for bulk electricity cost minimization. The motivation for this was to evaluate the effectiveness of pre-cooling a home prior to the DR event.

$$\min_{\boldsymbol{S},\boldsymbol{T}} \sum_{t=1}^{24\cdot 60} C_t S_t + \beta * \sum (T - T_{ub})^2 \qquad \forall\ T - T_{ub} > 0$$

$$\begin{array}{llll}
\text{s.t.} & T_0 = T(0),\ S_0 = 0 & & \text{(Initial condition)} \\
& T_{lb,t} \leq T_t & \forall\ t \in \{0, 1, ..., 24\cdot 60\} & \text{(Temperature bounds)} \\
& T_{t+1} = T_t + 60\big[\frac{1}{RC_p}(T_{\infty,t} - T_t) - \frac{S_t Q}{C_p}\big] & \forall\ t \in \{0, 1, ..., 24\cdot 60 - 1\} & \text{(Dynamics)} \\
& S_t = S_{t-1} = S_{t-2} = S_{t-3} = S_{t-4} & \forall\ t \in \{5, 10, 15, ..., 24\cdot 60\} & \text{(HVAC Constraint)} \\
& S_t \in \{0, 1\} & \forall\ t \in \{1, ..., 24\cdot 60\} & \text{(HVAC on/off)}
\end{array}$$

The objective function consists of two variables. The first being the cost of electricity which is depending on when the HVAC is on and the cost of energy at the moment it is on. The second is a penalty function that increases quadratically with the difference between the current temperature and the upper bound, based on the DR program. The greater the difference, the higher the penalty. The units for β are in $\$/°C^2$

[1] http://oasis.caiso.com/mrioasis/logon.do

The constraints are as follows, the first sets up the optimal control to have the HVAC turned off and the sets the internal temperature of the house. The second prevents the HVAC from doing too much pre-cooling and the bounds are based on the DR program. The third equation models the temperature of the house at every minute. The fourth equation ensures that if the HVAC is turned on it does so for at least 5 minutes, to prevent it from constantly switching on and off. Lastly the fifth equation initializes the setting of turning the HVAC on or off.

4.0 Discussion

4.1 Logit Model Results and Prediction

The SP survey yielded a total of 128 responses which were used to determine the optimal parameters and parameter estimates for the logit model. Utilizing maximum likelihood estimate (MLE), we determined the parameter estimates, which can be found under 'coef' in Table 3, allowing us to make general predictions about human behavior. Negative parameters represent decreased favorability while positive parameters represent increased favorability.

Table 3. Logit Model Results

	coef	std err	z	P>|z|	[0.025	0.975]
Reward, units:$10	0.1331	0.035	3.753	0.000	0.064	0.203
Days x Hours x Temperature, units: 10 days*hrs*F	-0.0170	0.007	-2.269	0.023	-0.032	-0.002
Temperature Change for local 80-90F, unit:F	-0.0777	0.033	-2.375	0.018	-0.142	-0.014
Temperature Change for local 90-100F, unit:F	-0.0905	0.032	-2.793	0.005	-0.154	-0.027
Democrat, unit:-	0.4897	0.198	2.477	0.013	0.102	0.877
CO2 Reduction, units:10%	0.1796	0.056	3.189	0.001	0.069	0.290
ac_Window Units, units:-	1.1467	0.396	2.896	0.004	0.371	1.923

Integrating these coefficients yielded the final logit equation below which was then used to generate predictions for the probability and share of people who would likely participate in a particular DR program design:

$$V_{opt\ in,n} = 0.1331\, X_{Monthly\ Incentive} - 0.0170\, X_{Days\times Hours\times \Delta T} - 0.0777\, X_{\Delta T,80-90°F} - 0.0905\, X_{\Delta T,90-100°F}$$

$$+0.4897\, X_{Democrat} + 0.1796\, X_{\%\ CO2\ Reduction} + 1.1467 X_{AC\ Window\ Unit(s)}$$

This model was then used to develop DR program prediction against Sacramento County. We determined that the only representation of population heterogeneity that could be captured with our model was affiliation with the Democratic party. Assuming all the households are uniformly distributed and that there is no variation in other characteristics (see Table 5 for exact values) among the population, we simplify our equation used to make predictions by sample enumeration to:

$$N_{opt\ in} = P(opt\ in \mid Democratic)P_{\%\ Democratic}X_{total\ households}$$

$$+P(opt\ in \mid not\ Democratic)(1 - P_{\%\ Democratic})X_{total\ households}$$

where $N_{opt\ in} = number\ of\ households\ that\ opt\ in$

$$P_i(opt\ in \mid Democratic) = probability\ of\ opting\ in\ given\ individual\ i\ is\ Democratic$$

$$P_{\%\ Democratic} = proportion\ of\ Sacramento\ population\ being\ Democratic$$

$$X_{total\ households} = total\ number\ of\ households\ in\ Sacramento$$

The following scenarios were developed for this prediction. The characteristics were determined using census, voter registration and weather data:

Tables 4: Prediction Scenarios and Characteristics

Scenario	Days	Hours	Temperature Change (°F)	CO_2 Reduction (%)
1	3	2	2.5	5
2	3	4	2.5	10
3	3	2	5	10
4	3	4	5	15

Table 5: Sacramento County Characteristics

Characteristic	Data
% Democratic	61.4
Average High Temperature (°F)	93
Total Households	571,949

Substituting in the constant values from our table, our prediction equation becomes:

$$N_{opt\ in} = P(opt\ in\mid Democratic) * 0.614(571949) + P(opt\ in\mid not\ Democratic) * 0.386(571949)$$

Applying the prediction equation to each of the prediction scenarios summarized in Table 4. gives us the expected market shares presented in Figure X. To achieve a 95% adoption rate, various degrees of incentives are needed, as shown in Table 6. Scenario 1 requires the least incentive per month whereas Scenario 4 requires the most incentive per month. We can see from the hours and temperature design that this makes sense as Scenario 1 has $5\ hr \times {}^{\circ}F$ for each day of the monthly program and Scenario 4 has $20\ hr \times {}^{\circ}F$, which is four times that of Scenario 1. Scenario 2 and 3 are very close in performance or preference, as we see from their near-overlap in Figure 4. and the same incentive approximation of $35/mo for 95% adoption. Interestingly, Scenario 2 is still comparatively more preferred compared to Scenario 3, which could indicate that a smaller temperature bound is much more preferable and important compared to the hour duration.

The results demonstrate people's willingness to participate in a low commitment program at low or even zero incentive amounts given the recognized environmental and social benefits. This factor was captured in the survey and model by % CO_2 reduction variable. However, a major limitation is that these are stated preferences, and reality there would likely be large attrition rates and temperature overrides during a DR event. In practice this shouldn’t distort the underlying economics because participants are not paid out if they override, it just means that active participation will be less than enrolled participation.

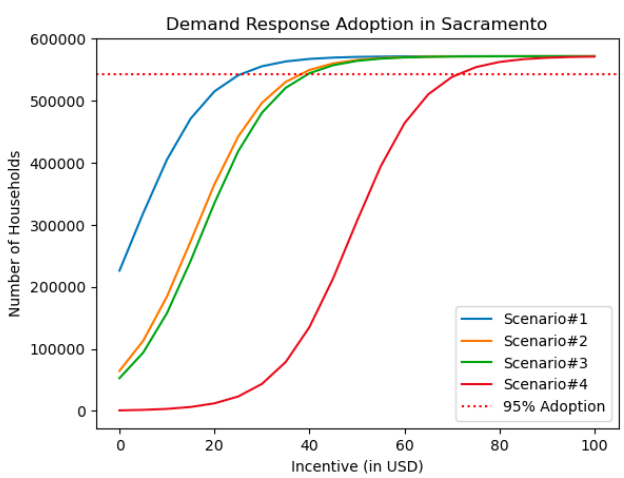

Figure 2. Incentive required to achieve 95% DR program adoption in Sacramento for each of the prediction scenarios

Table 6. Market Share Prediction Results for Sacramento using Table X1. Scenarios.

Scenario	Hours, Temperature	Incentive

1	2 hr, 2.5°F	$20/mo
2	4 hr, 2.5°F	$35/mo
3	2 hr, 5°F	$35/mo
4	4 hr, 5°F	$65/mo

4.2 Aggregated HVAC Model

Figure 3 shows the simulated temperature profile and HVAC on/off for a single household. Outdoor temperature is taken from Sacramento on September 6th, 2022. The simulation can easily be adjusted to account for different temperature setpoints, DR period, building parameters, and outdoor temperature. We use the results to calculate the hourly average kWh consumption profile of the HVAC system during the day.

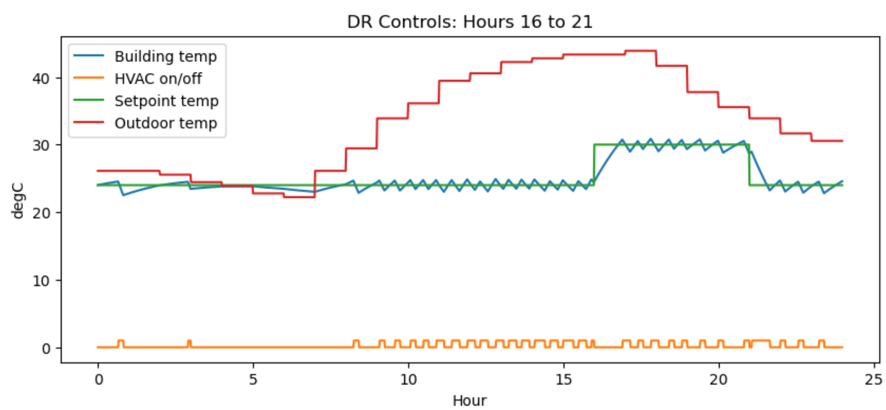

Figure 3: Single household HVAC simulation temperature profile results

500 homes with randomized parameters are simulated to obtain aggregated results for load profile change. We simulated the same 4 scenarios as described in Section 4.1, choosing the hours of the DR program to maximize savings based on the LMP of electricity in Sacramento on 9/6/22. For the 2 hour scenarios this was 6pm-8pm and for the 4 hour scenarios it was 5pm-9pm. Figure 4 shows the aggregated response profile Scenario 1: 2 hours, 2.5 °F change.

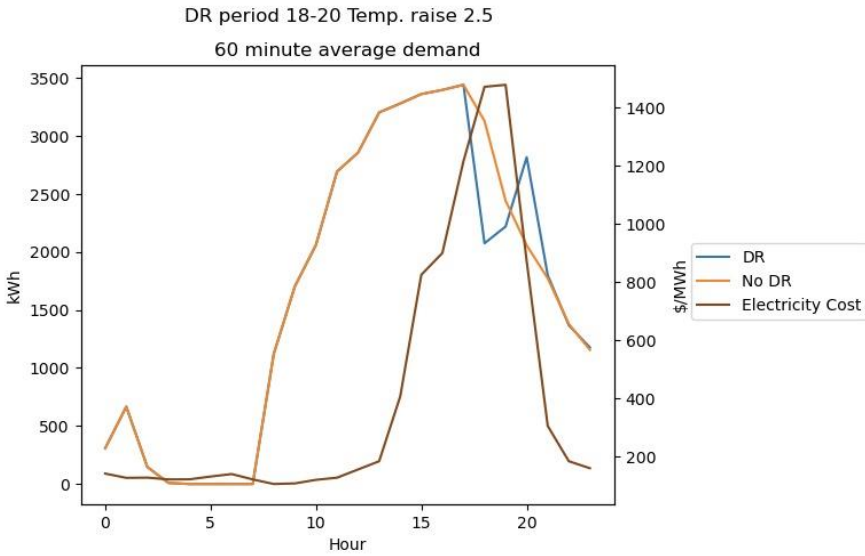

Figure 4: Aggregated HVAC load profile response for 500 simulated homes, Scenario 1. Context: Sacramento 9/6/22

Based on the aggregated results, we average the savings per household per scenario by extrapolating the results of a single day to the full month (3 days/month for each scenario). The resulting estimates for bulk electricity cost savings per household are given in Table 3. To enhance the accuracy of these results, simulations should be applied for multiple representative DR days (temperature profile and electricity cost) for the area of study.

Table 7: Expected bulk electricity cost savings per household from aggregated HVAC model

Scenario	Hours, Temperature	Expected Savings per Household
1	2 hr, 2.5°F	$6.3/mo
2	4 hr, 2.5°F	$10.7/mo
3	2 hr, 5°F	$12.4/mo
4	4 hr, 5°F	$21.0/mo

Comparing the results to the DR participation adoption rate for each program at varying incentive, we can conclude that Scenarios 1, 2, and 3 have significant participation rates at incentive rates below the expected monthly average savings, meaning the program would be advantageous and economically profitable. In particular, Scenario 1 generates the highest level of participation, and is our recommendation of the parameters for a DR program to adopt. Lower commitment temperature and hours are more agreeable and likely to be adopted by consumers, while still generating sufficient system benefits. Incentive ranges in the level of $5-$10 /month (along with the free smart thermostat(s)), should generate benefits commensurate with the costs of operating the program.

The expected savings may be biased in that they only reflect savings from a single, extreme day on California's grid. However, savings on bulk electricity generation costs is only one part of the benefit that demand response provides. Other benefits include:

- Better reliability and less risk of blackouts that can cause serious disruptions/deaths.
- Reduced reliance on combustion turbine "peaker" natural gas power plants.
- Reduced ability for generators to exercise market power.
- Better integration with renewable electricity generation.

Demand Response has the attention of policy makers, and with certain levels of subsidy and adjustments to market design (Market Access Program, CPUC) we confidently conclude this market has a bright future.

4.3 HVAC Optimal Control

The HVAC Optimal Control was set up following the parameters of scenario 2 and 4. The figure below shows the DR controls from 5pm to 9pm, September 6th 2022.

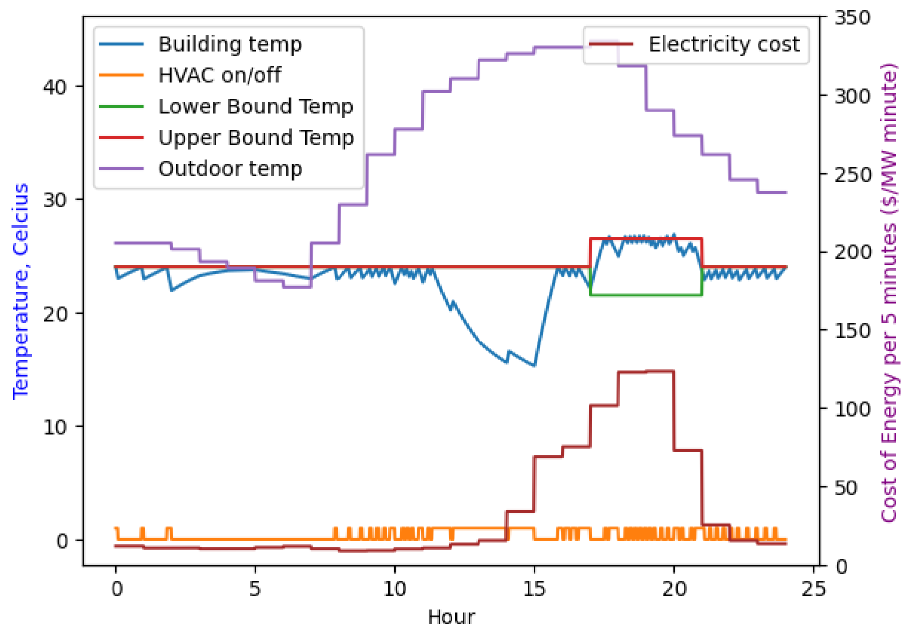

Figure 5: Temperature profile and cost of electricity for a home given Optimal HVAC Control for temperature bound 2.5°F Context: Sacramento 9/6/22

The β constant in the penalty function was set to 100, with the intention of ensuring that the building meets the temperature upper bound. The actual cost of HVAC Control during the DR period was based on the Locational Marginal Price was $10.61.

A similar process was done but with temperature bounds increased from 2.5 to 5 degrees was $8.73. This is expected since with the former condition, a lower temperature bound had to be maintained.

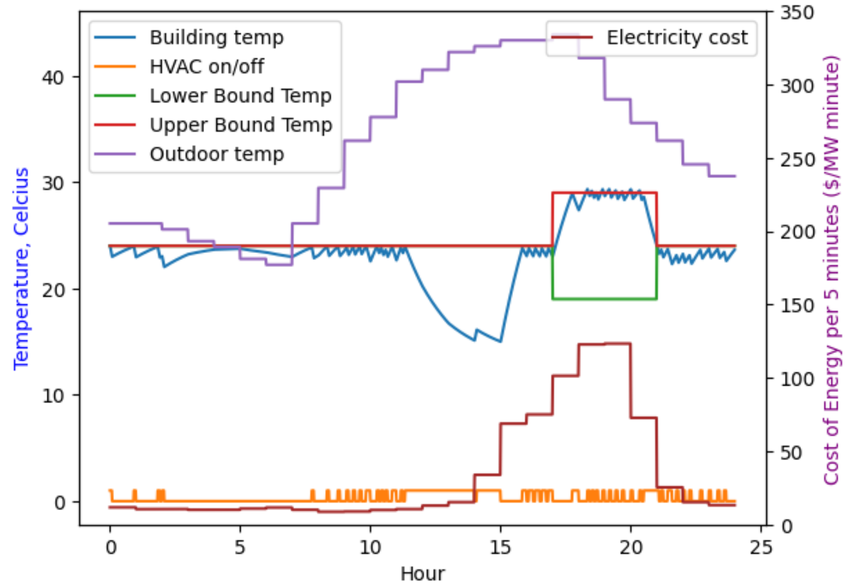

Figure 6: Temperature profile and cost of electricity for a home given Optimal HVAC Control for temperature bound 5°F Context: Sacramento 9/6/22

An interesting result that can be taken away from the plots is that pre-cooling the building earlier in the day prior to a period of high prices results in overall lower electricity costs. This would indicate that there could be additional benefits to demand response programs that consider pre-cooling in addition to simple temperature setpoint raises. This was not something we addressed in our survey or aggregated HVAC model, but we highlight this as a topic for future explorations.

5.0 Summary

This project conducted a stated preference survey to determine residential consumer's willingness to participate in HVAC control demand response (DR) programs based on different program designs. The design variables include the temperature setpoint increase of the participants thermostat(s), the hours per event, and number of events per month. Based on the survey results, a discrete choice binary Logit model is developed to estimate market share participation in the DR program. We further develop an aggregated HVAC simulation model to estimate bulk electricity procurement savings for a representative population of households participating in a DR event. Using the context of Sacramento, we estimate program participation rates and savings for 4 different scenarios of DR program design: Fixing 3 days per month, the scenarios are permutations of 2 vs. 4 hours per event and 2.5°F vs. 5°F setpoint change. The demand model results show high participation rates for lower commitment scenarios, and in particular 2.5°F and 2 hours had >40% participation when the incentive amount is just $5. The opt-in favorability is aided by a recognized social and environmental benefit captured in our behavioral model through survey response to a % CO_2 reduction variable. The costs are less than the expected $6.7/month in average household savings we calculate from the aggregated HVAC simulation. Based on these results, we recommend this lower commitment strategy for program design as a profitable economic endeavor. Demand response programs can be aided by subsidy to recognize the additional system benefits they provide. This project offers a scalable methodology that can be used by aggregators or utility companies to collect data and develop more accurate models from their customer base to forecast participation and savings for DR programs in their location. Our results from experimentation with optimal control point to the potential for increased benefit from pre-cooling buildings, and further studies could consider consumer's willingness to participate in HVAC control DR with pre-cooling.

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