#### What's Driving the CART in Behavior-Based Demand Response?

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## ABSTRACT

What happens when a large investor-owned utility asks everyone to reduce his or her energy use for a specific day? Do customers receive the message? Do they understand it? And, what do they do? This paper provides the results of a process evaluation of a Peak Time Rebate program that provided bill credits but no penalties to all residential and small commercial customers who reduced their energy use during specific event periods during the summer of 2012.

This evaluation used post-event surveys to assess overall event awareness, actions, and attitudes among several customer groups. A key aspect of the evaluation involved using classification and regression trees (CART) to model the relative importance and the interdependencies of customer characteristics, event awareness, and event behaviors in "driving" customers' actual event curtailment. Results indicate that customers have high levels of awareness around the overall concept and language used for event days, but that recollection drops off precipitously as respondents are asked about specific event dates. Event awareness was higher among those who had opted in to receive alerts, and among those who receive electronic communication from SDG&E. CART analysis confirmed that opting in for an alert is an important correlate of curtailment, but that overall, demographic and behavioral factors explain a relatively small proportion of curtailment. Residential customers generally regard PTR favorably and intend to curtail during future events, despite some dissatisfaction with the bill credit.

# Introduction

Utilities are increasingly offering demand response programs as a strategy for avoiding expensive investments in new generation or high priced market power. Demand response programs are designed to cause a reduction of energy use during peak demand periods, where market prices for power tend to be the highest and the least cost-efficient power plants are brought online.

San Diego Gas & Electric (SDG&E), with smart meter infrastructure fully deployed to all 1.2 million residential customers, has launched several programs designed to encourage behavior change at critical periods of peak demand by leveraging the enhanced visibility possible from linking detailed consumption data with web-based displays of consumer-specific information. This paper presents the results of an evaluation of the 2012 Peak Time Rebate (PTR) program, which offered bill credits for measured reductions in electricity use during specific time periods, but did not assess penalties for non-curtailment. The PTR program was designed to leverage SDG&E's Smart Meter infrastructure to encourage large-scale customer participation in demand response events and to begin to transform customer knowledge about time-dependent energy costs by introducing event-driven incentive rates to residential customers who have not traditionally been exposed to these types of rate structures.

One of the key characteristics of any smart grid demand response program is the extent to which the initiative relies on direct load control (DLC) devices or end user behavior to effect change. SDG&E, like other utilities, has both DLC and behavior-based programs (e.g., Mantei et al. 2012). One of the limits to wider deployment of DLC programs is the need to obtain permission from individual residential customers—getting them to agree to allow the utility to control major equipment (typically air conditioning settings) during critical peak periods. As these periods often occur during high

temperatures, participants can experience discomfort. In addition, the requirement to have air conditioning equipment can exclude large sections of the market. PTR, a voluntary, behavior-based program, allowed residential accounts to earn bill credits for energy saved on event days. The PTR program offers two levels of incentives: a basic level for customers who reduce through behavioral means and a premium level for customers who reduce through automated enabling technologies, like the DLC devices, which are registered with the utility.

SDG&E's PTR demand response program also leveraged its online account management system. Like most utilities, SDG&E offers residential customers an opportunity to pay bills and manage accounts on line using a MyAccount login option. Once a customer has set up MyAccount with SDG&E, they can access up to 25 months of account activity and information and have the potential to access detailed consumption data as uploaded by SDG&E's smart grid infrastructure. About half of SDG&E's 1.2 million residential customers have MyAccount.

### **Peak Time Rebate Overview**

San Diego Gas and Electric's 2012 Peak Time Rebate (PTR) rate allowed residential and individually-metered small commercial customers to earn a bill credit for reducing their energy use when requested by SDG&E during a specific time (CPUC 2008). Unlike most energy efficiency and demand response programs, customers did not have to enroll or sign up for anything to be eligible. Customers were paid 75¢ per kilowatt hour (kWh) reduction between the hours of 11:00 a.m. and 6:00 p.m. on event days, but penalties were not assessed for households that did not achieve a measurable reduction of electricity usage. To encourage customers to embrace automated enabling demand response technologies, customers enrolled in the Summer Saver air conditioning cycling program earned a premium incentive of \$1.25 per kWh reduced. Bill credits are calculated based on measured reduction in electric usage on an event day relative to an established customer-specific reference level (CRL) for that day. A customer's CRL is calculated by looking at their usage during the hours of 11 a.m. to 6 p.m. on the previous five days before the event day and averaging their usage on the three highest-use days. Weekdays are matched with weekdays and likewise for weekend days.

PTR events may be called when forecasted temperature and system load reach certain targets or when other grid emergencies occur. In addition, the California ISO may issue statewide Flex-Alert days during extreme heat waves or other grid emergencies that are independent of PTR's Reduce Your Use (RYU) days (events that cause capacity constraints in Northern or Central California do not necessarily constrain the San Diego system). Regardless of the location of capacity constraints, alerts for statewide Flex-Alert days are reported in San Diego media. To minimize the potential confusion with Flex-Alert days, PTR staff decided to call RYU days on all Flex-Alert days during the demand response season.

SDG&E called a total of seven Reduce Your Use day events during the summer of 2012, including two that were also Flex Alert days. Customers could sign up in advance ("opt in") to receive alerts either by email or text message. In addition to the opt-in alerts, SDG&E sent alert emails to all customers registered with MyAccount and announced events broadly using mass media (including television and radio announcements), social media, and press releases carried by other media outlets. As of September 2012, just over three percent of SDG&E's residential accounts had signed up to receive event alerts.

## **Evaluation Objectives and Methods**

Research Into Action conducted a process evaluation of the 2012 Peak Time Rebate rate. The objectives of this process evaluation were to: document and assess the implementation process and

identify opportunities to improve effectiveness; assess customer awareness of the program including perceptions of, and response to, curtailment requests; and evaluate the effectiveness of the messaging used in the program and suggest improvements to increase customer awareness and understanding. The evaluation team conducted interviews with program staff, three post-event surveys, a general survey assessing residential customer perceptions of PTR, and three focus groups.

Data collection centered on several aspects of awareness and understanding and included questions to assess:

- Overall awareness of Reduce Your Use events
- Customers' sources of awareness
- The relationship between opting in for an event alert and awareness or curtailment
- Customers' actions in response to event requests
- The extent to which reported behavior correlates with event performance

Table 1 provides the survey groups and sample sizes for residential survey data collection activities. All four surveys included Alert, MyAccount, and No MyAccount groups. In addition, the August and September surveys included samples of participants in two other SDG&E programs: San Diego Energy Challenge (SDEC), where participants signed up to compete to reduce energy use and win prizes for themselves and local schools as well as receiving PTR alerts, and Summer Savers, a DLC program cycling air conditioners in exchange for an annual incentive. This paper focuses on the data collected in the September post-event survey, but draws from other surveys where noted (see Research Into Action 2013 for the complete report). Note that the September survey used both phone and webbased data collection. This paper presents the differences between modes where applicable. Unless otherwise noted, results have been combined across survey modes.

Survey Type	Month Collected	Mode	Alert	MyAccount	No MyAccount	SDEC	Summer Savers
Post Event	July	Phone	202	100	100		
	August	Phone	155	70	68	68	70
	September	Phone	70	76	77	69	77
		Web	531	711	159	558	557
General	December	Phone	188	155	128		

**Table 1.** Residential Survey Groups

The availability of actual consumption data from SDG&E's advanced metering infrastructure provided the evaluation team with an opportunity to compare findings from the process surveys with actual curtailment performance. The evaluation team used CART analysis to assess the key drivers behind consistent curtailment and identify variables that could allow SDG&E to more effectively target Reduce Your Use messaging and encourage participation among those most likely to respond. CART, also known as recursive partitioning, builds a classification or regression model represented as a binary tree by recursively splitting the cases into two groups using the split that maximizes the variance explained. The overall model conveys the relative predictive strength of the independent variables relative to the outcome. We describe the CART analysis and results in more detail below.

# **Event Awareness, Behaviors, and Attitudes**

Surveys revealed that awareness of the overall Reduce Your Use message and concept was high, but that awareness of more detailed programmatic features (such as the bill credit opportunity or specific

event call dates) was lower. Unsurprisingly, those that had voluntarily opted-in to receive an alert on event days had the highest level of awareness.

Although awareness of event days was relatively low among those who had not opted in for an alert, overall event impressions were generally positive. Over three-fourths of contacts agreed that they would participate in the future, and over two-thirds of event-aware contacts reported making an effort to reduce their energy use on the most recent event day.

#### **Event Awareness**

While general program awareness is relatively high, awareness of programmatic details and event days appear to be driven by Alert and MyAccount status (Figure 1). Awareness of the RYU requests was relatively constant across the post event surveys, where the lowest levels of general request awareness were over 65% and the highest were nearly 100%. Respondents were less aware of programmatic details like the opportunity to earn bill credits and were often unable to recall the specific date of the RYU event. The higher awareness level among web survey respondents reflects the importance of email communication in event notification: contacts who received and responded to survey requests sent to their SDG&E-verified email address tended to be those who had received and opened their event alert emails.





General survey results further reveal differences in event awareness across groups (Figure 2). Approximately three months after the last event, over 90% of customers without MyAccount were unable to recall a single PTR event. In comparison, 86% of Alert group contacts recalled at least one event.





The sources of awareness and the desired method of notification differed substantially between those with MyAccount and those without (Table 2). Email was the largest source of information for MyAccount customers, while those without MyAccount were most likely to report hearing about RYU days on TV. The preferred means of notification also differed across response groups. Alert group contacts and MyAccount contacts preferred email and text message as means of awareness, while those without MyAccount preferred mail and TV. The large portion of the No MyAccount group that preferred notification by direct mail indicates that this group may be difficult to reach for the short-notice events that characterize demand response.

	Actual Means of Notification			Preferred Means of Notification		
	Alert (n=1179)	MyAccount (n=362)	No MyAccount (n=71)*	Alert (n=188)	MyAccount (n=155)	No MyAccount (n=128)
Email message	85%	83%	9%	86%	71%	40%
Direct mail	4%	6%	9%	26%	37%	55%
A text message	16%	3%	0%	53%	50%	33%
TV announcement	16%	22%	61%	25%	30%	41%
Auto phone call	N/A	N/A	N/A	29%	30%	35%
Radio	9%	12%	14%	19%	26%	27%
Newspaper			18%	10%	12%	21%
SDG&E website	2%	1%		26%	21%	11%
Facebook, Twitter				18%	22%	9%
Other web news				10%	19%	9%
Word of mouth	4%	4%	4%	N/A	N/A	N/A

Table 2. Actual and Preferred Method of Alert (Multiple Responses Allowed)

\* Due to low sample sizes, results are averaged across three post-event surveys.

Overall, alert status is an important variable in both level of awareness and engagement with PTR and SDG&E messaging. Additionally, the fact that customers with MyAccount have registered their email addresses with SDG&E makes them easier to reach and more likely to be aware of programmatic details than those without MyAccount.

### **Event Behaviors**

Only those aware of events were asked more detailed questions about event engagement. Among these contacts, a majority reported making an effort (68% overall, including 77% of alert group contacts). Those contacts who reported making an effort on event day reported what actions they took to save energy (Table 3). Among those who made an effort to reduce their energy use, 59% reported turning off lights in unoccupied areas of their home, 56% said they avoided doing laundry during the event time, and 54% turned off or adjusted their air conditioner. Other actions mentioned included avoiding running the dishwasher (38%), unplugging unused electronics (35%), leaving home (32%), and shifting cooking times (24%). An additional 50% reported they also "just tried to use less energy."

Table 3. Actions Taken During	g RYU Event (Mu	Itiple Responses A	Allowed)
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Action	Percent (n=687)
Turned off lights in unoccupied spaces	59%
Did not do the laundry	56%

Action	Percent (n=687)
Turned off or adjusted air conditioner	54%
Did not run the dishwasher	38%
Unplugged unused electronics	35%
Left home	32%
Cooked at a different time	24%
Pre-cooled the house	12%
Turned off pool pump	7%

Additionally, 52% of those contacts who were aware of events reported that, as a result of RYU days and the information they had received, they had subsequently made changes in their energy use outside of PTR event times. Common changes reported included turning off lights (31%), adjusting air conditioner settings (23%), and turning off unused devices (20%).

#### **Event Attitudes**

Those contacts who had made an effort to reduce their energy use reported on their primary motivation to do so (Figure 3). Given three possible motivations, overall, respondent selections were relatively evenly distributed between earning a bill credit (38% overall), doing my part for San Diego (34%), and helping the environment (28%). A majority of alert group contacts (59%) reported that earning a bill credit was their primary motivation, though.





Many of those contacts who had not made an effort to reduce their use on event day also offered reasons. The most common reasons for not making an effort were that they were already conserving energy, or that it was too hot to participate that day. Open-ended responses provided additional explanation of these barriers to reducing use on event days. In offering suggestions for how SDG&E could make events work better for customers, 16% of respondents provided comments about the circumstances that limited customers' ability to respond to events. The most frequently mentioned topic was that the respondent already makes a daily effort to conserve energy use (63% of these respondents). Over one-third of these contacts reported that there was nothing they could do to reduce energy on event days. Other comments included that customers would try within reason to conserve, that they made an effort but received no credit, that they found the campaign unfair to low energy users, and that medical or other household issues limited their ability to conserve. Just a few contacts reported that they did not want to participate.

Overall, contacts were satisfied with events and willing to participate in the future. While just half of contacts agreed that the value of the bill credit was reasonable, most of those contacted reported

they would be "very" or "somewhat" likely to participate in future events (including 92% of alert group contacts and 76% of others). Furthermore, contacts were receptive to the idea of opting in to receive event notifications: 93% of contacts said that they would be "somewhat" or "very" likely to sign up for notifications if it was required to receive a bill credit.

## **Curtailment Correlates**

A key component of this evaluation was understanding the extent to which reported effort on event days was correlated with greater observed curtailment, and the factors that moderated the effect of reported effort on actual curtailment.

Although the bill credit was based on the number of kWh curtailed during the seven hour event period, we hypothesized that demographic factors and external constraints such as house size likely drove a substantial portion of the magnitude of event day savings for customers. To try to isolate the effects of behaviors on curtailment, we explored three separate measures of performance in this analysis:

- kWh savings (the kWh saved during an event),
- binary savings (whether any kWh was saved during the event), and
- curtailment consistency (the number of event days out of seven with measured curtailment.)

The first two measures of performance quantify performance on a particular event day, while the third quantifies performance across all PTR events.

A preliminary examination of the relationship between effort and these three measures of event performance suggested that reported effort was only moderately correlated with actual event performance (Figure 4). One-third of those who reported making no more effort than usual to save energy during the September event (including those who were unaware of the event) had saved at least 1 kWh on the event day, compared with 43% of those who reported making a lot more effort than usual. These non-effort performers and high effort non-performers suggested that a considerable proportion of event performance could be due to chance: random variations in residential energy use. Similarly, those who reported making a lot more effort than usual to save energy on event day saved an average of 2 kWh, while those who reported making no effort saved an average of 1.4 kWh. Those who reported making a lot more effort saved energy on an average of 3.3 of 7 days, compared with 2.9 of 7 among others.



Figure 4. Proportion Curtailing, kWh Saved, and Days Curtailed by Reported Level of Effort

### **Analytical Approach**

To better understand which demographic and behavioral factors best associate with customers' curtailment during PTR events, we used Classification And Regression Tree (CART) modeling. This exploratory analysis examines the relative predictive strength of independent variables relative to a dependent variable, in this case, event performance (see Therneau & Atkinson 2012 for a more complete discussion of CART models). That is, these models would determine which demographic, attitudinal, or

behavioral factors are most strongly related to event performance, and also give us a sense of how well these predictors explained event performance.

We included 21 predictor variables in each model, including demographic factors (average kWh use, climate zone, home size, income, household size, presence of children under five, presence of children under 18, presence of seniors, home ownership, ethnicity, AC use, pool ownership); behavioral factors (alert opt-in, SDEC opt-in, MyAccount signup, number of actions taken, effort, logon to tracking website); and awareness and attitudinal factors (awareness of event, awareness of concept, motivation). Except for average kWh use, Alert and SDEC opt-in, and MyAccount signup, all variables were self-reported in the survey.

We used multiple regression to confirm the relationships identified in the CART models. Using the same independent variables (all of which were orthogonally coded or mean-centered) we recreated the interactions from the CART model as closely as possible. We then added additional demographic predictors and behavioral factors. To test whether the behavioral predictors were significant over and above the effect of the demographic predictors alone, we used stepwise regression, adding the demographic predictors first.

#### **Curtailment Consistency Metric**

We conducted a series of CART models with different transformations of the three outcome variables. Table 4 summarizes the results of the best CART model for each of the three outcome variables.<sup>1</sup> The overall predictive power of the "binary savings" model was very low, with an R<sup>2</sup> indicating that the model explained just 3% of the variance in whether or not customers curtailed on September 15. In fact, all models for this outcome variable predicted savings worse than chance. The overall predictive power of the total "kWh savings" model was moderate. This model explained 16% of the variance among those customers who saved at least 1 kWh on September 15.<sup>2</sup> The only two significant predictors in this model, though, were demographic predictors rather than behavioral or attitudinal ones. That is, while greater energy use was related to greater reduction in use, reported awareness of the event and reported actions to reduce energy use during the event were not significantly related to increased savings, among those customers who were able to save at least 1 kWh. Finally, the "curtailment consistency" model had modest predictive power (explaining 9% of the variance in the number of days curtailed), but included significant behavioral as well as demographic factors. Specifically, both opting in for an alert and opting in for the San Diego Energy Challenge predicted a greater number of days with measured curtailment. We therefore chose curtailment consistency as our measure of event performance.

Dependent Variable	Model $R^2$	Independent Variables in Best Model
Binary savings (any kWh event savings)	0.03	N/A
kWh savings (among those saving ≥1 kWh)	0.16	Average kWh use, AC
Curtailment consistency (number of days)	0.09	Average kWh use, Alert opt-in, SDEC opt-in

Table 4. September Event Regression Tree Explanatory Value

<sup>&</sup>lt;sup>1</sup> The best model was determined by "pruning" the initial tree according to the 1-Standard Error rule, choosing the simplest tree where the risk is within one standard error of its achieved minimum.

<sup>&</sup>lt;sup>2</sup> Because the kWh saved variable is highly skewed, we examined whether, among those contacts who had saved any energy during the event, behavior and attitudinal factors were related to the amount of savings. See Research Into Action 2013.

### **CART Results**

Figure 5 shows the regression tree for the model predicting curtailment consistency (the number of days reduced, out of seven). Each rectangle, or node, is a variable where the tree splits. The labels below each node show the split points for the variable. Regression trees model the best "split" for continuous independent variables, such as average monthly kWh use. The circles are terminal leaves in the tree, the model's estimate for the number of days reduced by that subset of customers. Light colors indicate lower curtailment consistency, while dark colors indicate higher curtailment consistency.

Here, we have shown the best (black) and complete (gray) regression tree for curtailment consistency among the September 15 sample. Although we cannot conclusively say that the gray branches are meaningful predictors of curtailment consistency, we include them here because of the story they tell about the interaction between demographic and behavioral factors.



Figure 5. Regression Tree (Predictors of Curtailment Consistency, Data September 15 Sample)

Note: Black nodes are part of best model. Gray nodes not part of the best model, but each increase  $R^2$  by  $\ge 0.005$ .

The CART analysis suggests several takeaways about curtailment consistency:

Low use customers may not be suited for this program. For customers using less than 260 kWh per month, opting in to receive an alert or to the SDEC program do not significantly predict greater consistency of event performance. There is a small subset of customers (n=18) in our sample who use between 167 and 260 kWh per month who reduced their use an average of 4.3 out of 7 days, by trying very hard (that is, they reported performing at least 6 of the 10 actions we listed during the 9/15 event). Among Alert opt-ins, those with energy use above 477 kWh per month, particularly those who used air conditioning, had higher average consistency than others.

**Voluntary engagement is important.** Among those customers using more than 260 kWh a month, signing up to receive alerts or enrolling in the SDEC program does predict increased performance consistency, relative to others. Among those who did not opt-in, those that reported tracking their performance via the website also had more performing days than their non-tracking counterparts (an average of 3.8 of 7 versus 3 of 7 days).

Overall, this model suggests that engagement with RYU events played a role in how many days customers were able to curtail, but that the largest predictor of consistent curtailment is average monthly electricity use.

### **Regression Analysis Results**

Subsequent multiple regression analysis generally confirmed the CART results. Stepwise regression suggested that demographic and behavioral factors combined predicted performance consistency better than demographic factors alone (the demographics-only model explained 6.4% of the variance in curtailment consistency, while the combined model explained 10.9% of the variance).<sup>3</sup> Regression also confirmed that in addition to kWh use, opting in for an alert plays a role in curtailment consistency, but that Alert opt-in has a greater effect on consistent curtailment for higher users (Table 5). Unlike the CART results, though, the main effect of effort was a significant predictor in the regression model. (Note that because effort and number of actions were correlated r=.66, we included only effort, not the number of actions, in the regression model.) In the CART model, reported event day behaviors only appeared for those with low energy usage.

	Term	Standardized Coefficient (Beta)	р
	Intercept		.000
Demographics	MyAccount	.008	.794
	Home ownership	.064	.047
	Household income	.025	.444
	Ethnicity	027	.344
	Number of occupants	.044	.175
	Climate zone	037	.198
	Children under 5 present in household	.016	.602
	Average kWh use	.199	.000
Behaviors	Event day effort	.070	.025
	Alert opt-in	.136	.000
	San Diego Energy Challenge participant	.091	.002
	Logon to website	.048	.121
Interaction Terms	Average kWh Use * Alert opt-in	.081	.022
	Alert opt-in * Logon to website	006	.857
	Effort * Alert opt-in	011	.751
	Average kwh use * Effort	027	.454
	Effort * Alert opt-in * Average kWh use	021	.557

Table	5	Regress	ion (	oeffi	cients
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## **Conclusions and Recommendations**

The PTR process evaluation identified several key decisions facing SDG&E and other utilities that might consider a territory-wide behavior-based rate credit for voluntary demand response that

<sup>&</sup>lt;sup>3</sup> Demographics-only model:  $R^2 = .064 F(9,1178) = 8.92$ , p <.001; Complete model:  $R^2 = .109 F(18,1169) = 7.94$ , p <.001.  $\Delta R^2 = .045 F(9,1169) = 6.58$ , p <.001.

results in measured curtailment. While respondents were generally satisfied with their experience and did not resent being asked to curtail their energy use during RYU days, comparing survey results with the energy consumption reduced relative to customer reference baseline revealed the limitations of assuming that measured curtailment would correlate with reported awareness and action. Based on these findings we provide the following recommendations for behavior-based demand response programs:

**Require an action to receive a bill credit.** Opting in for an alert was the most important behavioral factor affecting curtailment performance across multiple event days. Opting in for an alert is important for two reasons. First, lack of awareness and information is a key barrier to participation, and opting in for an alert virtually ensures event notification. Second, opting in for an alert likely reflects increased overall engagement with SDG&E generally and PTR specifically because of the commitment represented in the simple action of registering for alerts.

**Target recruitment: some segments are very hard to reach, and others can do little to participate.** Event awareness among customers without MyAccount lags behind awareness among those with MyAccount. Television is an effective alert tool for a portion of these contacts, yet many of these customers prefer mail notification of events, indicating a lack of understanding about demand response as well as a lack of engagement. Additionally, low users (260 kWh a month and below) generally only receive incentives through extraordinary effort. Some low users (both actual and perceived) feel disadvantaged by the program and want recognition for their daily efforts to conserve energy.

Align incentives with existing motivations. The per-kWh incentive used in the PTR program has both positives and negatives: some customers found the kWh feedback motivating, but for others, the incentive was not well-aligned with community or environmental motivations to participate, and engendered frustration that the program is unfair to low energy users. In addition, the payment per event is generally small – less than a few dollars – and may focus participants too much on the specific payment associated with what might be extraordinary effort. Providing a seasonal incentive for everyone that curtails for a certain number of days or saves above a threshold level could allow a larger one-time payment (such as \$10). Providing an incentive for enrolling in voluntary alerts could also tap into the bill credit interest reported by the alert group while also encouraging more wide spread enrollment in alerts.

Develop a strategy for encouraging on-going energy savings or encouraging more engagement with premise-level consumption. At least half of contacts who were aware of PTR events reported making day-to-day changes to reduce their energy use. Similarly, for a notable segment of customers, PTR created a desire for more information about their household's energy use. These may be opportunities for utilities to leverage demand response programs to increase participation in other programs, including detailed feedback strategies available through in-home displays or with enhanced websites.

#### **Evaluation Lessons Learned**

Matching survey results to impact data can help give a more complete picture of which customers are engaging with the program, and the factors that are most correlated with successful curtailment. The CART model was also a good analytical tool. From a methodological perspective, it helped isolate those variables that explained the most variance in curtailment consistency. From a practical perspective, it generated an easily-visualized segmentation of participants. The outcome of the CART model was more accessible and more actionable than a regression model, which revealed relationships between variables but not cut points or direct indicators of relative importance.

There are some practical considerations in implementing this approach in other evaluations. We found that memories of these demand response events faded quickly, and thus the post-event survey approach was useful in maximizing response accuracy. We also found that while web surveys enable the

large sample sizes that such data mining approaches require, using utility database email addresses can introduce bias, particularly when email is the primary means of program alerts. Furthermore, from a process perspective, single demand response events provide only a partial picture of how customers engage with PTR.

Finally, there are several cautions to using the CART methodology (Therneau & Atkinson 2012; Maimon & Rokash 2010). Most fundamentally, CART requires very large sample sizes. CART models are optimized on a per-split basis, not on a model basis, so there is a risk of over-fitting. Multiple highly correlated variables are unlikely to appear in the same model. RPART is also slightly biased toward variables with more levels. Despite these limitations, though, the use of CART as a tool for exploratory data analysis provided an interesting framework to understand how customers engaged with these demand response events.

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