Executive Summary of the 2011 SDG&E Measurement and Evaluation Load Impact Reports

June 1st, 2012

SDGE

A Sempra Energy utility℠

Contents

1 SDG&E's 2011 Load Impact Executive Summary

In Decision (D.) 08-04-050 the Commission required San Diego Gas & Electric Company (SDG&E) to perform annual studies of its demand response (DR) activities using the load impact protocols and to file the entire load impact reports by April 1st each year. The load impact protocols require the preparation of numerous tables and as a result the load impact reports were too large to be filed in hard copy. The electric investor-owned utilities filed a petition to modify the D.08-41-050 on April 6th 2009 to request the requirement to file the load impact reports in their entirety be removed and replaced with a requirement to provide the reports to the energy division of the CPUC. On April 8th 2010 D.10-04-006 granted the utilities permission not to file the entire load impact reports, but also directed the utilities to file an executive summary of the load impact reports.

SDG&E submits this executive summary in accordance with D.10-04-006. This report contains a summary of the ex-post and ex-ante load impacts of the SDG&E Capacity Bidding Program (CBP), Critical Peak Pricing Default (CPP-D), Summer Saver program and the Peak Time Rebate pilot. The critical peak pricing emergency (CPP-E) program was active in 2011, but no events were called and this program has been canceled beginning in 2012. In addition this summary contains an ex-ante forecast for the permanent load shifting (PLS) program and the Small Customer Technology Development Program (SCTD). This report includes a summary of the ex-ante forecasts for these new demand response activities. The last section of the report describes the portfolio analysis done to account for dual participation between CPP-D and other demand response programs. The summary ex-ante tables that include the 10-year forecast for the 1 in 2 individual program scenario, the 1 in 2 portfolio scenario, the 1 in 10 individual program scenario, and the 1 in 10 portfolio scenario are provided in a separate document named Appendix A.

2 Summary of SDG&E's Capacity Bidding Program Report

2.1 Program Description

This report documents the results of an ex post and ex ante load impact evaluation of the Capacity Bidding Program (CBP) of San Diego Gas & Electric (SDG&E), for Program Year 2010. The program has two options Capacity Bidding Program day-ahead (CBP DA) and Capacity Bidding Program day-of (CBP DO). Customers may also choose a maximum event length of 4 hour, 6 hour, or 8 hours. The program is available from May through October and events may be called any time between 11 am and 7 pm. Results for the day-ahead and day-of options were forecasted separately. In this program aggregators contract with commercial and industrial customers to act on their behalf with respect to all aspects of the DR program. This includes receiving notices from the utility, arranging for load reductions on event days, receiving incentive payments, and paying penalties to the utility. Each aggregator forms a "portfolio" of individual customer accounts such that their aggregated load participates in the DR programs.

2.2 CBP Ex-Post Results

There were 48 meters that were nominated during 2010 in the CBP DA program and 318 meters that were nominated in 2011 in the CBP DO program. The table below shows the accounts nominated, percentage load reduction, aggregated load impact the temperature, and the nominated load reduction.

Estimated Ex Post Load Impacts by Event Day
2011 SDG&E CBP Events

Program	Event Date	Accounts	% Load Reduction	Aggregate Load Impact (MW)	Average Temp. During Event	Nominated MW
CBP-DA 1-4 Hour	07/05/2011	40	39.0%	8.3	76.5	8.0
	08/26/2011	51	38.7%	10.1	76.2	8.0
	09/07/2011	50	46.6%	14.0	82.5	7.6
	10/12/2011	50	49.2%	13.3	83.7	7.2
	10/13/2011	50	44.5%	11.2	74.2	7.2
	Average Event	**48**	**43.9%**	**11.3**	**78.7**	**7.6**
CBP-DO 1-4 Hour	07/05/2011	247	17.0%	7.3	75.6	8.9
	07/06/2011	247	17.6%	7.6	76.8	8.9
	08/26/2011	236	17.6%	7.1	75.3	8.2
	09/07/2011	247	22.4%	10.6	83.0	8.3
	09/09/2011*	247	14.4%	5.7	64.2	8.3
	10/12/2011	247	15.1%	6.5	87.3	8.4
	10/13/2011	247	14.1%	5.9	74.8	8.4
	Average Event	**245**	**17.0%**	**7.2**	**76.7**	**8.5**
CBP-DO 2-6 Hour	07/05/2011	72	20.5%	4.3	75.8	2.6
	07/06/2011	72	19.5%	4.1	76.9	2.6
	08/26/2011	72	19.8%	4.2	75.6	2.6
	09/07/2011	73	22.0%	5.0	83.2	2.6
	09/09/2011*	73	20.1%	4.0	64.3	2.6
	10/12/2011	73	19.6%	4.1	87.6	2.6
	10/13/2011	73	21.0%	4.3	75.1	2.6
	Average Event	**73**	**20.4%**	**4.3**	**76.9**	**2.6**

2.3 CBP evaluation methodology

To calculate load reductions for demand response programs, customer's load patterns in the absence of program participation – the reference load – must be estimated. incorporate research design elements into the analysis and statistical modeling.

With the aggregator programs, the primary intervention is present on some days and not on others, making it possible to observe behavior with and without events under similar conditions. This type of repeated treatment supports a "within subjects" analysis design in which impacts are determined by comparing differences in peak period electricity use on event days and on similar days when events are not called. This approach works if customer behavior on "event-like" days is similar to their behavior on event days. This underlying assumption can be made with reasonable confidence for weather insensitive customers. However, more caution is required in evaluating impacts for weather sensitive customers. The aggregator programs tend to be dispatched on high system load days when temperatures are well above average. A critical task of the evaluation is to ensure that factors that may correlate with hotter temperatures are not confounded with demand reductions.

Individual customer regressions were the primary method used to estimate ex post load impacts. The analysis consisted of applying regression models separately to each set of customer load data at the half-hourly level – 48 models for each customer.1 An alternative specification would be to run a single model for each customer with every term interacted with each half-hour interval. Running 48 separate models produces coefficients and standard errors that are arithmetically equivalent to the outputs produced by the single model with half-hourly interactions, but the 48 separate models are easier to interpret and using this approach produces intermediate outputs that can be synthesized more quickly. The regression coefficients are specific to each customer and half-hour. Since each customer is analyzed individually, the approach accounts for factors that are constant for each customer, such as industry and geographic location. It also better explains the variation in individual customer production and/or occupancy patterns, weather sensitivity, price responsiveness, enrollment dates and event day dispatch patterns (which can vary by customer).

To determine the most accurate model specification, a two-step process was implemented. In step 1, the goal was to select the model that best explained electricity

[1] Since SCE provided only hourly load data, regression models were applied separately to each set of customer load data at the hourly level, producing 24 models for each customer.

use patterns under event-like conditions using out-of-sample testing. In step 2, a false experiment was used to ensure that bias was minimized in the selected model. A false experiment model includes a treatment variable, like an aggregator dispatch day, for event-like days. If the model is correctly specified, the coefficients for false event-day variables should be insignificant and centered around zero because, in fact, there are no events.[2] If the coefficients are significantly different from zero, the regression model is confounding error with event impacts, leading to bias in the impact estimates.

The following model specification was used for ex post impact estimation:

$$kw_h = \alpha_h + \beta_h \cdot 24hrCDH_h + \beta_h \cdot CDH_h + \sum_{i=1}^{3} \beta_{i,h} \cdot daytype_i + \sum_{i=5}^{10} \beta_{i,h} \cdot month_i + \beta_h \cdot daylight_h + \beta_h \cdot morningload_h + \beta_h \cdot twoweekavg_h + \sum_{i=1}^{n} \beta_{i,h} \cdot AMPorDRRCevent_i + \sum_{i=1}^{m} \beta_{i,h} \cdot CBPevent_i + \varepsilon_h$$

Term	Description
α	Represents the regression model constant for the interval.
β	Represents regression model coefficients.
24hrCDH	Reflects the effect of heat build-up over the past 24 hours on electricity use. This is captured by calculating the total cooling degree hours over the past 24 hours, using a base of 65˚F.
CDH	Reflects current temperature by calculating current cooling degree hours, using a base of 65˚F.
daytype	Is an indicator of whether the interval in question falls on the first day of the business week, mid-week, or on the last day of the business week. Weekends and holidays were excluded from the ex post regression.
month	Is an indicator of the month of the year. It is included to capture seasonal variations in non-weather sensitive electricity use.
daylight	An indication of the percent of the interval in daylight (1 = full day, 0 = full night, fractions are during dusk and dawn).
morningload	Reflects the total kWh consumed between midnight and 9 AM; the same day of the interval in question.
twoweekavg	The average kW for the interval in question during all non-holiday, non-weekend, non-event days in the past two weeks.
AMPorDRRCevent	An indicator of whether an AMP or DRRC event was called that day. There is an indicator for each event specifically (*i.e.*, AMP event 1, AMP event 2). This variable takes into account whether the customer was nominated for participation. A customer that is not nominated for participation is assumed not to have been activated for the event.
CBPEvent	An indicator of whether a CBP event was called that day. There is an indicator for each event specifically (*i.e.*, CBP event 1, CBP event 2). This variable takes into account whether the customer was nominated for participation. A customer that is not nominated for participation is assumed not to have been activated for the event.

[2] More specifically, the false event coefficients should be statistically insignificant for 95% of customers.

2.4 CBP Ex-Ante Analysis

Ex ante forecasts of load impacts for SDG&E were produced based on per-customer load impacts calculated from the ex post evaluation results, and applied to enrollment forecasts provided by the utilities. This section documents the preparation of ex ante forecasts of reference loads and load impacts for 2011 to 2020 for the SDG&E CBP program. Separate load impact forecasts were developed for the *day-ahead* and *day-of* program types, where relevant.

To produce ex ante impacts, we did the following for each customer:

- Estimated the regression parameters from the ex post regression models. This included parameters that described customer hourly load patterns, individual event load impacts, and how load impacts varied for each event under different weather conditions;

- Calculated the average event hour impacts for each customer across all events, as well as the average load shift in the hours preceding and following an event ("event shoulders"). Additionally, we calculated the model error and performance variability of customers over many events;

- Assumed the 1-in-2 and 1-in-10 weather year conditions based on the location of each customer;

- Replicated the same variables used in the ex post regression models;

- Predicted the customer electricity use patterns absent event day response – reference loads – based on the regression coefficients and ex ante event-day conditions; and
- Predicted the hourly electricity use pattern with event day response - the estimate load with DR – based on the average event hour impacts and the average pre- and post-event load shifting under ex ante event-day conditions.

Impacts were calculated as the difference in loads with and without DR. They were aggregated for the program as whole, for each local capacity area, and for each customer size category Load impacts were projected only for May through October when the program is available. Each industry group was expanded at the same rate over time, corresponding to the enrollment forecast provided by SDG&E, which specified the number of enrolled customers within each program type (*e.g.*, DA and DO, and event window length). The enrollment forecast predicts that the program load impacts will grow by 10% between 2011 and 2012, 5% between 2012 and 2013 and 5% between 2013 and 2014.

Aggregate Ex Ante August Peak Day Load Impacts for SDG&E CBP (Hourly Average Reduction from 1 to 6 PM)

Weather Year	Year	Nominated Accts (Forecast)	Agg. Load Impact (MW)	% Load Reduction	Weighted Temp (F)
CBP-DA	2012	54	12.7	52.0%	82.4
	2013	57	13.5	52.0%	82.4
	2014 - 2022	60	14.2	52.0%	82.4
CBP-DO	2012	338	12.3	16.3%	82.1
	2013	357	12.9	16.3%	82.1
	2014 - 2022	375	13.6	16.3%	82.1

3 Summary of SDG&E's Critical Peak Pricing Default Report

3.1 CPP-D Rate Description

This report documents the results of a load impact evaluation for program-year 2010 of the SDG&E CPP-D rate. The primary goals of the evaluation were to estimate the hourly ex-post load impacts achieved on each event day and to provide ex-ante forecasts of the load impacts expected to be achieved by CPP-D for 2012-2021. SDG&E implemented CPP-D in 2008 with an "opt-out" provision and bill protection, and began transitioning previous volunteers onto the new default rate.

SDG&E's default CPP takes on different values for different rate classes. The default CPP rate is a commodity-only rate and customers pay all non-commodity charges according to their otherwise applicable tariff. Customers on SDG&E's default CPP are allowed to pay a monthly capacity reservation charge (CRC) that limits the amount of their load that is exposed to CPP prices on event days. In addition, customers receive a bill protection guarantee for the first year, during which their bill under default CPP is guaranteed not to exceed what it would have been had they opted out to the new otherwise applicable tariff. Events for the SDG&E CPP-D rate last from 11am-6pm and can be called on any day of the year.

3.2 CPP-D Ex-Post Results

SDG&E only called two CPP events in 2011 and one was on a weekend. The first event occurred on August 27, a Saturday, and the second was held on September 7, a Wednesday. There were 1,291 accounts enrolled during the first event and 1,293 enrolled for the second event. The participant weighted average temperature during the peak period was 80°F for the weekend event and 86°F for the weekday event.

Table 6-1 shows the estimated ex post load impacts for each event day. Not surprisingly, there was a substantial difference in the reference load for the weekday and weekend events. The estimated reference load for the weekday event was 276 MW, nearly 33% higher than for the weekend event. However, the percent load reduction, at 6.3%, was higher on the weekend than the 5.2% estimate for the weekday event. As such, there was only about a 10% difference in the aggregate demand response for the two event days. On the weekend event day, August 27, the aggregate load reduction equaled 16.9 MW, while the September 7 weekday impact equaled 18.6 MW. It should be noted, however, that with only two data points, one on a weekend and the other on a weekday, it is difficult to conclude with certainty that SDG&E CPP customers were more price responsive (on a percentage basis) on the weekend. A more prudent approach would be to assume that the two-day average percentage impact is a better estimate for both days. However, the absolute load reduction is likely to be greater on weekdays because of the significantly higher reference load.

Estimated Ex Post Load Impacts by Event Day
2011 SDG&E CPP Events

Event Date	Number of Participants	Average Reference Load (kW)	Average Load with DR (kW)	Average Load Impact (kW)	% Load Impact	Aggregate Load Impact (MW)	Average Temperature During Event (°F)
8/27/2011	1,291	208.4	195.3	13.1	6.3%	16.9	79.5
9/7/2011	1,293	277.5	263.1	14.4	5.2%	18.6	86.3

3.3 CPP-D Evaluation Methodology

Regression models meant to capture the relationship between electricity use, year, day type, season and weather were run for each customer. Ordinary Least Squares regression was used and a separate model was run for each hour.[3] Eight specifications were tested and the final results for each customer are based on the specification that produced the least bias for that customer. The eight models vary in how weather variables were defined, if at all, and in the inclusion of monthly or seasonal variables. This tailored approach customized models based on whether or not customers were weather sensitive or exhibited seasonal patterns.

[3] Running separate models each hour – 24 models – with robust standard errors using OLS produced similar standard errors as time series techniques including Feasible GLS and Newey-West correction for auto-correlation.

Table 3-1: Regression Model Variables

Variable	Description
kW	Energy usage in each hourly interval t={1,2,3 …24} for each date, d
Year	Binary variable for year of the hourly observation
Daytype	Binary variable for the day type of the hourly observation (Sundays and holidays and Tuesday through Thursday are grouped together
Season	Binary variable indicating whether the hourly observation falls in the summer or winter season
Month	Binary variable indicating the month of the hourly observation
Otherdr	Binary variable indicating the presence of another DR event
Actcpp	Binary variable identifying the pre and post-enrollment periods on CPP as distinct
CDH	Cooling Degree Hour - the max of zero and the hourly temperature value less a base value
HDH	Heating Degree Hour - the inverse of CDH
CDD	Cooling Degree Day - the max of zero and the mean temperature of the day of the hourly observation less a base value
HDD	Heating Degree Day - the inverse of CDD
Totalcdh	The sum of cooling degree hours for the date of the hourly observation
Totalhdh	The sum of heating degree hours for the date of the hourly observation
Eventday	Binary variable indicating whether the day of the hourly observation is an event day
eventdayXtotalcdh	The interaction between whether the day of the hourly observation is an event day and totalcdh
$\text{eventdaynum}_{1 \ldots n}$	Binary variables indicating each event day, 1 ...n.

CPP-D Ex Ante Load Impacts

Whenever possible, ex ante load impacts are grounded on analysis of historical load impact performance. The ex-ante impacts are based on the similar models used for the ex post analysis but includes all 2010 and 2011 events in order to better inform the event impact coefficients. By including events from prior years, the ex ante regressions are better able to account for variation in impacts across different weather conditions.

Large C&I Ex Ante Impact Development

For large customers, the degree of uncertainty for ex ante load impacts has narrowed substantially because they have already been defaulted and bill protection period has expired for almost all large customers. We now know how many of these customers tried out default CPP, how much load reduction they provided during events, what types of customers were more responsive and how many remained on CPP at the end of the summer. In addition, while some changes in enrollment will occur as newly defaulted customers determine if CPP is the right rate for them, the customer mix for large CPP is expected to remain relatively stable.

For the most part, the ex ante load impacts for large customers describe the load reduction capability of existing resources under a standard set of 1-in-2 and 1-in-10 weather conditions. To produce ex ante impacts, for each continuing customer, we:

1. Stored the regression parameters from the multi-year ex post regression models. This includes parameters that describe customer hourly load patterns, weather sensitivity, average event load impacts absent weather, and how load impacts vary under different weather conditions;
2. Linked the 1-in-2 and 1-in-10 weather year conditions to each customer based on their location. For example, in predicting the 1-in-2 August Peak Day impacts for a customer in the Greater Bay Area and one in Fresno, the ex-ante weather conditions reflected their local conditions.
3. Replicated the same variables used in the ex post regression models;
4. Predicted the customer electricity use patterns absent event day response – i.e. the reference loads – based on the regression coefficients and ex ante event-day conditions; and
5. Predicted the hourly electricity use pattern with event day response – the estimate load with DR – based on the regression coefficients and ex ante event-day conditions.
6. Accounted for changes in enrollment and customer mix, such as the mandatory default of PG&E's agricultural and SMB customers to PDP.

Impacts were calculated as the difference in loads with and without DR. The reference loads and impacts were then weighted to reflect any changes in enrollment levels and/or mix. Finally, they were aggregated for the program as whole and for each local capacity area. We produced both program specific and portfolio impacts. Portfolio impacts apply attribution rules to ensure dually enrolled customer impacts are not double-counted in the portfolio. In general, programs with a higher degree of commitment are attributed load impacts. For example, impacts for a customer dually enrolled in an aggregator program and CPP would be attributed to the aggregator program because it involves a contractual commitment to deliver specific amounts of load reduction.

3.3.1 Medium C&I Ex Ante Impact Development

For medium customers, the magnitude of ex ante impacts under default dynamic pricing is less certain than it is for large customers. Outside of California, no utility in the U.S. has defaulted medium customers onto dynamic pricing tariffs. Within California, several hundred of the 250,000 medium customers have been defaulted onto CPP, mostly in SDG&E, but it is necessary to account for differences between them and the far larger population of medium customers scheduled to default onto CPP.

To estimate medium customer impacts, we relied on customers that had already been defaulted onto CPP that were most similar to medium customers. To obtain a larger and more diverse sample, customers with average hourly demand below 100 kW throughout the year were combined with medium customers.4 In other words, customers that are only slightly above the large customer threshold were used as a proxy for medium customers. This is possible for three reasons. First, across all three utilities medium customer rates (20-200 Max kW) are very similar to the rates of customers in the next size category (200 to 500 Max kW). For SDG&E, the tariffs are nearly identical. the CPP prices that drive the load reductions are similar to those of large customers. Second, a substantial number of customers are slightly above the large customer threshold. Third, there is substantial overlap in the electricity use patterns and industry mix between medium and large customers.

To produce ex ante impacts, we applied the same five step process described in Section 3.2.1, but excluded any customer that voluntarily enrolled in CPP prior to the default period. There were two primary differences in producing the final impact estimates. First, the estimating sample was weighted by industry and climate region to reflect the distribution of medium customers. Second, the estimating sample load shapes were

---

[4] Customers are classified as small, medium and large based on maximum demand levels rather than average demand levels. As a result, many customers with average demand of 100 kW and below may look more like medium customers. In addition, some customers that met the definition of large customers, at the time, were defaulted onto CPP, but no longer meet the definition of large customers. Many of these customers remain on CPP rates.

rescaled to the size of medium customers. In other words, in producing medium customer ex ante impacts, we accounted for differences in the size, industry mix and geographic distribution between the estimating sample and the larger medium customer population.

The biggest shifts in ex-ante impacts for medium customer occurred because of updated assumption regarding customer enrollments. SDG&E updated their enrollment forecast to better reflect the medium customer population that will be defaulted onto CPP. Last year, they assumed all SDG&E customers on AL-TOU, the current standard rate for medium customers, would be defaulted. This year, they included and additional crosscheck to ensure the customers fit the official SDG&E definition of a medium customer. By doing so, the enrollment forecast avoided incorrectly including small customers that had voluntarily enrolled on AL-TOU.

Since SDG&E existing customers enrolled on CPP-D have already been on the program at least one year without bill protection it is not necessary to estimate how many customer will opt-out due to losing bill protection. However, due the potential energy shortages this summer some customers may opt-off the CPP-D rate this year because they may be concerned there will be many CPP-D event this year. Therefore the enrollment forecast predicts that 12% of existing customers will opt-out in 2012. Since medium customers have not yet been defaulted onto CPP-D it is necessary to estimate participation rates for them. Since these customers will receive bill protection their first year these rates are lower for the second year than the first year.

Medium CPP-D participation rates			
Industry	**1st year**	**2nd year**	**3rd year**
Agriculture, Mining & Construction	77%	65%	61%
Manufacturing	74%	60%	56%
Wholesale, Transport, other utilities	88%	82%	77%
Water Districts	86%	79%	74%
Retail stores	76%	63%	60%
Offices, Finance, Services	76%	64%	60%
Hotels and Apartment Buildings	62%	43%	41%
Schools	72%	57%	53%
Institutional/Government	73%	58%	55%
Other or Unknown	76%	64%	60%
TOTAL	76%	64%	60%

The SDG&E CPP_D load impact forecast for the August monthly peak day for large and medium CPP-D is presented in the tables below.

Aggregate Portfolio Annual Peak Day Load Impacts for Large SDG&E CPP Customers
(Hourly Average Reduction in MW Over 11AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Load impact (MW 11 am-6 pm)	% Load Reduction (MW 11 am-6 pm)	Weighted Temp (MW 11 am-6 pm)
1-in-2 August System Peak Day	2012	1154	11.4	3.0%	78.7
	2013	1170	12.1	3.1%	78.7
	2014	1185	12.7	3.2%	78.7
	2015	1201	13.0	3.2%	78.7
	2016	1218	13.2	3.2%	78.7
	2017	1235	13.3	3.2%	78.7
	2018	1252	13.5	3.2%	78.7
	2019	1270	13.6	3.2%	78.7
	2020	1287	13.8	3.2%	78.7
	2021	1305	13.9	3.2%	78.7
	2022	1324	14.1	3.2%	78.7

Aggregate Portfolio Ex Ante Annual Peak Day Load Impacts for Medium SDG&E CPP Customers
(Hourly Average Reduction in MW Over 11 AM to 6 PM)

Weather Year	Year	Enrolled Accts (Forecast)[1]	Avg. Load impact (MW 11 am-6 pm)	% Load Reduction (MW 11 am-6 pm)	Weighted Temp (MW 11 am-6 pm)
1-in-2 August System Peak Day	2012	-	-	-	-
	2013	-	-	-	-
	2014	9513	23	6.9%	82.6
	2015	7096	14	5.7%	82.5
	2016	6317	13	5.7%	82.5
	2017	6403	13	5.7%	82.5
	2018	6493	13	5.7%	82.5
	2019	6581	13	5.7%	82.5
	2020	6674	14	5.7%	82.5
	2021	6765	14	5.7%	82.5
	2022	6856	14	5.7%	82.5

4 Summary of SDG&E's Summer Saver Report

4.1 Summer Saver Program Description

San Diego Gas & Electric Company's (SDG&E) Summer Saver program is a demand response resource based on air conditioning load control. It is implemented through an agreement between SDG&E and Alternate Energy Resources, formerly known as Comverge, and is currently scheduled to continue through 2016.

The Summer Saver program is available to residential customers and commercial facilities that use up to a maximum of 100 kW on average during a 12-month period. The Summer Saver season runs from May 1st through October 31st and does not notify participating customers of an event. A Summer Saver event may be triggered the day of an event if warranted by temperature and system load conditions. Events may be called at any time between 12pm and 8pm and have a maximum length of 4 hours. There are a variety of enrollment options for both residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time, and can have cycling occur only on weekdays or on weekends as well. Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive paid for each option varies and is based on the number of air conditioning tons being controlled at each site.

4.2 Summer Saver Ex Post Load Impact Estimates

Six Summer Saver events were called in 2011. The events were each four hours long and began at either 1 PM or 2 PM. A blackout began between 3 and 4 PM on September 8, limiting all load impact estimation for that day to the period 1-3 PM.

Date	Aggregate Load Impacts (MW)			
	Cycling Option			
	Residential		Commercial	
	100	50	50	30
26-Aug-11	5.8	4.3	2.8	1.6
7-Sep-11	10.5	8.5	2.5	1.4
8-Sep-11	10.0	9.2	3.3	1.5
9-Sep-11	3.1	2.7	1.5	0.6
12-Oct-11	6.5	5.4	2.2	1.5
13-Oct-11	9.5	8.7	2.2	1.1
Average	7.6	6.3	2.4	1.3

4.3 Summer Saver Methodology

The primary source of information used in both the 2009 and 2010 evaluations of Summer Saver for reference load was load observed during non-event times. This was significantly aided by the experimental design put in place for settling the demand response contract with Comverge Inc. Under this contract, a stratified, random load research sample of residential and commercial Summer Saver customers was created. During each event, half of the load research sample would be held back to provide reference load (i.e. those CAC units would not be controlled during the event). Individual customer regressions performed well under these conditions because any given customer in the sample had several event periods during which their load could act as reference load because it was not curtailed. Moreover, even if particular events were unique from all other event days (such as September 27, 2010, which was the hottest day of 2010 and the all-time SDG&E system peak), load from one half of the sample could be used to estimate the reference load for the other half in a treatment-control analysis rather than individual customer regressions.

Each customer has a different usage pattern over time, and each customer's usage is likely to respond differently to changes in weather. For this reason, separate regressions were estimated for each premise in the residential sample,5 but using a common regression specification over all cases. For all premises, the factors used to estimate usage patterns were weather variables interacted with time indicators. These allow the model to take into account different reactions to weather conditions at different times of day, times of week and times of year. For example, a residential customer's energy usage might respond strongly to high temperatures on a Saturday afternoon when they are at home, but it might not respond at all on a Wednesday afternoon when they are at work.

Only non-holiday weekdays were modeled because no events were called on either weekends or holidays, and weekend usage behavior is quite different from weekday usage. Table 3-4 defines the variables and describes the effects they seek to identify. The regression specification was:

$$
\begin{aligned}
kWh = a &+ \sum_{i=1}^{24}\sum_{j=5}^{10} b_{ij} \times lagcdh_i \times hour_i \times month_j + \sum_{i=1}^{24} c_i \times hour_i + \sum_{i=1}^{24} d_i \times wacdh_i \times hour_i \\
&+ \sum_{i=14}^{20} e_i \times wacdh_i \times earlyevent_i \times hour_i + \sum_{i=15}^{21} f_i \times wacdh_i \times lateevent_i \times hour_i \\
&+ \varepsilon
\end{aligned}
$$

[5] As discussed in Appendix A, this regression specification was also estimated for commercial units but the results were not ultimately the ones chosen.

Table 3-4: Description of AC Load Regression Variables

Variable	Description
a	Estimated constant
$b - f$	Estimated parameter coefficients
$hour$	Indicator variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior and event impacts
$month$	Indicator variable for the month
$earlyevent$	Indicator variable to model the hourly effects of events occurring during 1 PM - 5 PM
$lateevent$	Indicator variable to model the hourly effects of events occurring during 2 PM - 6 PM
$lagcdh$	Weighted average of the previous 24 hours of cooling-degree hours with a base of 70°F
$wacdh$	Weighted average of the previous 3 hours of cooling-degree hours with a base of 75°F. Captures shorter-term effects of high temperatures.
ε	Error term

Day-matching for Commercial Customers

Day-matching methods were used to produce commercial ex post impact estimates. Under this method, each event day was matched with a non-event day that appeared to provide an accurate reference load based on pre-event, event-period and post-event loads. A day's load had to satisfy three basic criteria to be judged to be suitable as a reference load for an event day:

- The event day average loads during the three hours before the event had to be at least as close to the average loads on the reference day during the same hours as they were to the average loads during those hours on any other non-event weekday. In other words, there was no day with pre-event average loads closer to those on the event day than the reference day chosen;
- The event day loads during the event hours had to be below the loads on the reference day during the same hours; and
- The event day loads during the three hours immediately after the event had to be near to or higher than the loads on the reference day during the same hours.

September 7 and August 26 had such high loads that no non-event day had loads that satisfied all the criteria. This was also true for using day-matching to model the impacts of the first two hours of the event on September 8, which was interrupted by the blackout. For these cases, the non-event day with the highest load was chosen and a same-day adjustment was applied. A same-day adjustment is a way to account for known biases in a reference load. In this case, the fact that that load in the hour immediately before the event is much higher than the highest available reference day load indicates the high likelihood of a downward bias in the reference load during the event. To partially correct this bias, the reference load is adjusted by adding to it the difference between event day load and the reference day load during the hour immediately before the event. This adjustment is calculated separately for each cycling option of each customer segment and applied to the day-matching reference load for each event day.

The table below shows the days that were chosen to provide reference load for each ex post event day. .

Event Days and Matched Reference Load Days for Commercial Customers

Event Day	Matched Days
26-Aug-11	2-Aug-11
7-Sep-11	2-Aug-11
8-Sep-11	2-Aug-11
9-Sep-11	7-Jul-11
12-Oct-11	6-Sep-11
13-Oct-11	25-Aug-11

Having identified matched days, load impacts for each cycling option within each customer segment were estimated by subtracting average hourly load during each event from average hourly load during the same hours of the matched reference day. Standard errors were calculated at an hourly level as the square root of the sum of squared standard errors of each hourly average load.

4.4 Ex Ante Summer Saver Load Impact Estimates

The models described above were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2012 through 2022. Enrollment is not expected to change in the future, so the tables below represent predictions for the whole period 2012 through 2022. FSC was provided with data by SDG&E that represents weather under 1-in-2 and 1-in-10 year conditions for each monthly system peak day.[6]

[6] The typical event day is an hourly average of the weather during the top 9 system load days in a 1-in-2 year and in a 1-in-10 year.

The ex ante event window is from 1 to 6 PM, which is the CPUC resource adequacy window.

Summer Saver Residential Ex Ante Impact Estimates

Day Type	Per CAC Unit (kW)		Aggregate (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.48	0.41	14	12
May Monthly Peak	0.39	0.17	11	5
June Monthly Peak	0.34	0.09	10	3
July Monthly Peak	0.52	0.42	15	12
August Monthly Peak	0.48	0.38	14	11
September Monthly Peak	0.83	0.64	24	19
October Monthly Peak	0.47	0.38	14	11

Summer Saver Commercial Ex Ante Impact Estimates

Day Type	Per CAC Unit (kW)		Aggregate (MW)	
	Weather Year		Weather Year	
	1-in-10	1-in-2	1-in-10	1-in-2
Typical Event Day	0.40	0.36	5.1	4.6
May Monthly Peak	0.33	0.24	4.3	3.1
June Monthly Peak	0.37	0.24	4.8	3.1
July Monthly Peak	0.39	0.36	5.0	4.7
August Monthly Peak	0.40	0.36	5.1	4.6
September Monthly Peak	0.48	0.42	6.2	5.4
October Monthly Peak	0.34	0.30	4.3	3.9

5 Summary of SDG&E's Base Interruptible Program Report

5.1 Program Description

SDG&E BIP is a voluntary program that offers participants a monthly capacity bill credit in exchange for committing to reduce their demand to a contracted FSL on short notice during emergency situations. SDG&E offers two options that vary with respect to the notification period, number and duration of allowed events and incentive payments:

- BIP-A (Option A): Requires load reduction response within 30 minutes. Incentive payments are $7/kW. The maximum event length is 4 hours per day and the maximum number of events is 10 per month and 120 hours per calendar year; and
- BIP-B (Option B): Requires load reduction response within three hours. Incentive payments are $3/kW. The maximum event length is 3 hours per day and the maximum number of events is 10 per month and 90 hours per calendar year. This option will no longer be available beginning in 2012.

5.2 BIP ex-post results

SDG&E called a BIP event on August 18, 2011 that lasted from 12 PM to 4 PM for BIP option A customers and 3 PM to 6 PM for the single BIP option B customer. Option A customers received 30-minute notice of the event and Option B customers received 3 hours. In total, 21 customers participated in the event.

Aggregate Load Impact for August 18, 2011 SDG&E Event

Customer Category	Number of Customers	Load Reduction (MW)	% Load Reduction
All Customers	21	2.40	34.8

5.3 BIP Evaluation Methodology

With DR resources for which there is little event history like BIP, this regression-based method cannot be used to predict load reductions because there is not enough empirical event data for estimating the impact coefficients. However, for ex ante load impact estimation purposes, regression analysis can be used to predict the reference load (i.e., the load that would occur in the absence of a program event), and the expected load reductions from those customers given their FSL. For ex post load impact estimation purposes, regression analysis can be used to predict the reference load for the historical event day; the actual metered load for that day can be subtracted from the reference load to estimate the load impact. For ex ante analysis, the estimated load reduction for BIP is a function of: Forecasted load in the absence of a DR event (i.e. the reference load);

The participant's FSL; and Over/under performance relative to the FSL.

The reference load is estimated using the regression model discussed below. Over/under performance, which is a measure of how well customers perform during BIP events relative to the FSL, is determined for each industry using historical event data.

The dependent variable in the regression model was the kW load in each hourly interval for each participant. The regression model contained hundreds of variables, consisting largely of shape and trend variables (and interaction terms) designed to track variation in load across days of the week and hours of the day. Weather variables were tested and had significant impacts for certain customers. Binary variables representing when the underlying TOU rates changed during the day and season were also included to capture the change in load due to price variation. The regression model is as follows:

$$
\begin{aligned}
kW_t = {} & A + B \times SummerOn_t + C \times SummerMid_t + D \times SummerOff_t + E \\
& \times WinterMid_t \\
& + \sum_{i=1}^{24}\sum_{j=1}^{5} F_{ij} \times Hour_i \times DayType_j + \sum_{i=1}^{24}\sum_{j=1}^{12} G_{ij} \times Hour_i \times Month_j + \\
& + \sum_{i=1}^{24} H_{ij} \times Hour_i \times TotalCDH_t + \sum_{i=1}^{24} I_{ij} \times Hour_i \times TotalCDHsqr_t \\
& + \sum_{i=1}^{24} J_{ij} \times Hour_i \times TotalHDH_t + \sum_{i=1}^{24} K_{ij} \times Hour_i \times TotalHDHsqr_t \\
& + \sum_{i=1}^{24} L_i \times Hour_i \times Other\_Eventday_t \\
& + \sum_{i=1}^{24}\sum_{j=1}^{2} M_{ij} \times Hour_i \times BIP\_Eventday_j + e_t
\end{aligned}
$$

Table 3-1:
Variable Descriptions

Variable	Description
kW_t	hourly BIP customer load at time t
A	estimated constant term
B through M_{ij}	estimated parameters
$SummerOn_t$, $SummerMid_t$, $SummerOff_t$ and $WinterMid_t$	binary variables that indicate which TOU rate block is in effect for each hour
$Hour_i$	series of binary variables for each hour, which is interacted with all of the remaining variables because each has an impact that varies by hour
$DayType_j$	series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday)
$Month_j$	series of binary variables for each month
$TotalCDH_t$	total number of cooling degree hours (base 70) per day
$TotalCDHsqr_t$	total number of cooling degree hours per day squared
$TotalHDH_t$	total number of heating degree hours (base 70) per day
$TotalHDHsqr_t$	total number of heating degree hours squared
$Other\_Eventday_t$	binary variable for event days from other DR programs
$BIP\_Eventday_j$	binary variable representing each BIP event day;[7]
e_t	error term

[7] SCE and SDG&E had one event during the time period included in the estimation, whereas some PG&E BIP participants had two events.

5.4 BIP ex-ante Load Impact Forecast

For SDG&E's over/under performance analysis, data for the 2011 BIP event was used. Data for multiple years was not pooled together, as in PG&E's over/under performance analysis, because SDG&E's program has changed substantially in recent months. In fact, several customers that historically provided relatively large load impacts have left the program since the 2011 event. Therefore, SDG&E's over/under performance analysis is based on data for the 2011 BIP event, specifically for the 17 customers that are still enrolled in the program. Among the 17 customers that are still enrolled in the program, the aggregate hourly impact during the event period was 1.02 MW and performance was 23.2%. Considering that these customers are representative of the current program, the 23.2% performance value is what was used for the ex ante analysis.

The table below shows the aggregate on-peak ex ante load impact estimates for each day type by weather year and forecast year. In accordance with the revised resource adequacy hours, the peak period is defined as 1 PM to 6 PM for the typical event day and the April through October monthly peak days and 4 PM to 9 PM for the November through March monthly peak days.

Weather Year	Day Type	Peak Period	2012	2013	2014	2015-2022
1-in-2	Typical Event Day	1-6 PM	1.39	3.24	5.09	5.71
	January Peak	4-9 PM	0.54	1.27	2.36	3.36
	February Peak	4-9 PM	0.71	1.77	3.18	4.37
	March Peak	4-9 PM	0.72	1.93	3.38	4.47
	April Peak	1-6 PM	1.10	3.11	5.30	6.77
	May Peak	1-6 PM	1.00	3.01	5.02	6.20
	June Peak	1-6 PM	1.14	3.09	5.04	6.02
	July Peak	1-6 PM	1.31	3.28	5.25	6.09
	August Peak	1-6 PM	1.37	3.19	5.01	5.63
	September Peak	1-6 PM	1.73	3.80	5.87	6.40
	October Peak	1-6 PM	1.98	4.15	6.31	6.68
	November Peak	4-9 PM	1.81	3.63	5.44	5.60
	December Peak	4-9 PM	1.46	2.81	4.16	4.17

6 Summary of the Peak Time Rebate Pilot

The SDG&E PTR pilot differs from most previous PTR pilots in that participants were randomly selected and assigned to the program rather being asked to volunteer. Three Thousand Pilot participants were chosen by SDG&E so as to be representative of all residential customers in the service area. Participants were informed of their selection and given information on the pilot and on ways that they might benefit by reducing usage when events were called.

The PTR pilot had the following features:

- Up to 9 events could be called, where the event window was 11 a.m. to 6 p.m.[8]
- Enrolled customers were notified on the day prior to events by automated phone messaging, and could also request notification through email or text message. They were encouraged to sign up through a website to receive electronic notification.
- The bill credits that participants were eligible to receive depended on whether they used automated enabling technology installed through a SDG&E program.[9] The basic rebate level was $0.75 per kWh, with a premium level of $1.25 / kWh for customers with enabling technology.
- Each participant received one of two types of introductory educational packages; one emphasized the *financial benefits* ("rewards") of reducing usage during PTR events, while the other emphasized the potential *environmental benefits* associated with such reductions in consumption.
- Reductions in energy consumption for rebate calculations were measured relative to a customer-specific reference level (CRL) that was based on an average of their consumption during the same period on previous days.[10]

---

[8] SDG&E's planned full-scale program will have no limits on the number of events, but will target 9 events for the year.
[9] The only available automated enabling technology was the air conditioner cycling devices already installed for Summer Saver (SS) participants.
[10] Specifically, usage reductions during event hours were measured relative to a customer-specific reference level (CRL) defined as consumption during the event window hours averaged over the highest 3 out of the most recent 5 similar non-event weekdays. The highest days are defined to be the days with the highest total consumption between 11 AM and 6 PM. The similar days exclude weekends, holidays, and other

6.1 Ex-Post PTR pilot results

Five PTR events were called in 2011. Four of the five PTR event days (September 7 and 8, and October 12 and 13) were also SS event days, although the SS events applied only to the relatively small subset of PTR-SS and Control-SS customers. Only one PTR-only event was called (August 28, a Sunday). All PTR events spanned the seven-hour period from 11 a.m. to 6 p.m., while all SS events were four hours in duration, covering the period of either 1 p.m. to 5 p.m. or 2 p.m. to 6 p.m. Of note, a system-wide outage began between 3 and 4 p.m. during the September 8 event, which caused all customers' loads to drop to zero for the remaining event hours. While results for the hours prior to the outage are included in the study, they are not discussed in detail. Two of the events were called on hot days in mid-October, by which time customers' average on-peak usage was substantially lower than in August and September, likely due to less frequent use of air conditioning. SDG&E usually calls demand response events on weekdays in the months of July, August and September, therefore the PTR event on September 7th was the only "typical" demand response event.

Overall, the study found that those PTR pilot participants *without* enhanced technology (*i.e.*, PTR-NT) reduced their electricity usage by about 1 percent to 5 percent across the five PTR events compared to Control-NT customers, after adjusting for other differences between the two groups. These findings are summarized in Table ES-1, which shows average temperatures, event hours, percentage load impacts, and average hourly load impacts per customer. For the most "typical" summer weekday event (September 7), PTR participants reduced their usage by 4.5 percent, which translates into an *average hourly* reduction over the seven-hour event of 0.06 kWh per hour per customer. Information on the statistical precision of the estimated load impact coefficients indicates

---

PTR event days, and exclude other demand response program event days for customers participating in multiple demand response programs. The CRL for a weekend or holiday event is defined as the consumption during the PTR event period for the highest day from within the immediately preceding three (3) weekend days.

that an 80 percent confidence interval around the estimated 4.5 percent reduction in energy usage on September 7 ranges from 2.6 percent to 6.4 percent.

Overall PTR-NT Estimated Load Impacts and Event Characteristics

	Event Date				
	28-Aug	7-Sep	8-Sep	12-Oct	13-Oct
Ave. Temp. (11am - 6pm)	83.7	92.7	91.6	93.5	89.5
Event Hours (Hour Ending)	12-18	12-18	12-15[1]	12-18	12-18
Estimated Load Impact (%)	2.5%	4.5%	5.1%	3.3%	1.2%
Ave. Hourly LI (kW)	0.031	0.056	0.057	0.027	0.011

[1]Event truncated by outage

6.2 PTR evaluation methodology

Christensen Associate Energy Consulting tested several alternative customer-level regression models, including a panel approach for each climate zone/usage level zone cell, which included load data for all participant and control group customers from each cell. Based on these tests, they concluded that the most straightforward and appropriate approach to obtaining load impact estimates at the needed level of detail (e.g., by climate zone and in total) was to estimate separate aggregate-level models for each of the twelve climate zone/usage level cells (i.e., using load data for the average customer in each cell), using data for both participant and control group customers. They then aggregate those cell-level results to the climate-zone and overall program level using appropriate sample weights.

The models that were used to produce the estimated load impact results described in Section 4.2 below are specified in terms of differences between hourly loads averaged over the relevant participant and control group sample customers in each climate-zone/usage-level cell. That is, the dependent variable in the regression is the above difference in the hourly load of the participant and control groups, rather than the level of usage of participants, which is the more common approach that has been used in previous California load impact evaluations.

They use similar types of explanatory variables as in a typical ex post load impact regression, including hourly indicator variables interacted with each event day, weather variables, load shape variables, and day-type and month indicator variables. Using this design, the estimated event-day coefficients represent direct estimates of participant load impacts that account for estimated differences between the loads of participant and control group customer groups. This approach effectively amounts to a standard "difference-in-differences" evaluation approach. That is, estimated load impacts are represented by differences between participant and control group loads on event days, while controlling for estimated differences between the load profiles of the two samples under non-event day conditions.

The general form of the *ex post* load impact difference model is the following:

$$
\begin{aligned}
DQ_t &= a + \sum_{Evt=1}^{E} \sum_{i=1}^{24} (b_{i,Evt} \times h_i \times PTR_t) + \sum_{SSEvt=1}^{SSE} \sum_{i=1}^{24} (b_i^{SS} \times h_i \times SS_t) + \sum_{i=1}^{24} (b_i^{CDH} \times h_i \times CDH_t) \\
&+ \sum_{i=1}^{24} (b_i^{WECDH} \times h_i \times WECDH_t) + \sum_{i=1}^{24} (b_i^{CDH2} \times h_i \times CDH^2{}_t) + \sum_{i=1}^{24} (b_i^{LagCDH} \times h_i \times LagCDH_t) \\
&+ \sum_{i=2}^{24} (b_i^{MON} \times h_i \times MON_t) + \sum_{i=2}^{24} (b_i^{FRI} \times h_i \times FRI_t) + \sum_{i=2}^{24} (b_i^{h} \times h_i) + \sum_{i=2}^{24} (b_i^{WE} \times h_i \times WE_t) \\
&+ \sum_{i=2}^{7} (b_i^{DTYPE} \times DTYPE_{i,t}) + \sum_{i=6}^{10} (b_i^{MONTH} \times MONTH_{i,t}) + e_t
\end{aligned}
$$

In this equation, DQt represents the difference between the average hourly usage in time period t of the participants and control group samples for a particular climate zone/usage level cell; the b's are estimated parameters; hi is an indicator variable for hour i; PTRt is an indicator variable for PTR event days (and takes on a value of 1 only for participants); CDHt is cooling degree hours;11 WECDHt is cooling degree hours interacted with an indicator variable for weekends; CDH2t is cooling degree hours squared; LagCDHt is cooling degree hours from the same hour in the previous day; MONt, FRIt, and WE are indicator variables for Monday, Friday, and weekend days respectively, where the

[11] Cooling degree hours are defined relative to a reference temperature of 60 degrees. In all cases, customer-specific weather variables are calculated using data for the appropriate climate zone.

interaction with the hourly indicators allows estimation of different load shapes for those day types (an additional set of hourly indicators not interacted with other variables is included to represent the load profile for Tuesday through Thursday)12; DTYPEi,t is a series of indicator variables that allow constant adjustments for each day of the week; $MONTH_{i,t}$ is a series of indicator variables for each month; and e_t is the error term.

The term with the double summation signs is the component of the equation that allows estimation of *hourly load impacts* (the $b_{i,Evt}$ coefficients) for each event day. It does so via the hourly indicator variables h_i interacted with the event variables (indicated by PTR_t), where the coefficients reflect hourly differences between the participant and control group loads on event days (with that convention, participant event-day load reductions below control group levels would be represented by negative coefficients). The remaining terms in the equation are designed to control for weather and other periodic factors (*e.g.*, hours, days, and months) that determine the difference between PTR and control-group customer loads. The interaction of Monday, Friday and weekend indicators with the hourly indicators is designed to account for potentially different hourly load profiles on the first and last days of the workweek, and on weekends.

6.3 PTR Ex-Ante Forecast

SDG&E will roll out PTR to all of its residential customers in 2012. The steps to moving from the pilot results to a full program forecast are listed below.

Define data sources
Reference loads are developed using data for customers enrolled in the PTR pilot during 2011. The percentage load impacts that are applied to the reference loads to create hourly load impacts are based upon a combination of the ex post load impacts from the PTR

[12] Note that the hour indices for some sets of interacted variables include all 24 hours, while the hourly indicator variables (including those interacted with day type) exclude hour 1. Excluding one of the hourly variables is required in these cases in order to avoid perfect multicollinearity among the included variables (*e.g.*, when an hourly regression equation includes a constant term, it cannot also distinguish between an exhaustive list of all hours; one must be excluded).

2011 ex post evaluation and simulations using the load impact models from the statewide pricing pilot..

Simulate reference loads

In order to develop reference loads, we first re-estimated regression equations for the average customer in each cell defined by climate zone. Separate equations were estimated for the summer months of May through October, and for the remaining non-summer months. These equations were then used to simulate reference loads by customer type under the various scenarios required by the Protocols

Apply percentage load impacts to reference loads for each event scenario. In this step, the percentage load impacts were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts.

Apply forecast enrollments to produce program-level load impacts. SDG&E provided enrollment forecasts representing the eligible residential customers who will be automatically enrolled in PTR, and assumptions regarding the percentage of "aware" customers (50%). Program-level results were obtained by aggregating results across cells.

Ex-Ante forecast 1 in 2 weather year (MW)

Month / Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
January Peak	18.8	19.0	19.2	19.4	19.7	19.9	20.1	20.3	20.6	20.8
February Peak	16.6	16.8	16.9	17.1	17.3	17.6	17.7	17.9	18.1	18.3
March Peak	13.2	13.3	13.5	13.6	13.8	13.9	14.1	14.3	14.4	14.6
April Peak	10.6	10.7	10.8	10.9	11.1	11.2	11.3	11.4	11.6	11.7
May Peak	35.8	36.1	36.5	37.0	37.4	37.8	38.3	38.7	39.1	39.5
June Peak	40.8	41.2	41.6	42.1	42.6	43.1	43.6	44.1	44.6	45.0
July Peak	43.0	43.4	43.9	44.4	45.0	45.5	46.0	46.5	47.0	47.5
August Peak	44.6	45.0	45.5	46.1	46.6	47.2	47.7	48.2	48.7	49.2
September Peak	51.2	51.7	52.3	52.9	53.6	54.2	54.8	55.4	56.0	56.6
October Peak	43.7	44.1	44.5	45.1	45.6	46.2	46.7	47.2	47.7	48.2
November Peak	15.8	15.9	16.1	16.3	16.5	16.7	16.9	17.1	17.3	17.4
December Peak	18.9	19.1	19.3	19.5	19.8	20.0	20.2	20.4	20.7	20.9

7 Small Customer Technology Deployment (SCTD) Program

7.1 Program Description

SDG&E's Small Customer Technology Deployment (SCTD) Program will offer automated DR enabling technologies at no cost for up to 15,000 participating SDG&E residential customers. SDG&E proposes using Smart Meter interval data to identify, market to, and install load control devices in the homes of residential and small commercial businesses with significant air conditioning and residential customers with mid-day pool pump usage. These automated enabling technologies will provide incremental load reduction benefits during demand response events and create a technology platform that will support future dynamic pricing rate design for residential and small commercial customers. Potential end use loads include central air conditioning, refrigeration, lighting, pool pumps and electric water heaters.

The residential load impact forecast for the SCTD program quantifies the load impacts of programmable communicating thermostats (PCTs) and pool pumps. The residential load impact estimates provided are incremental to the PTR load impacts.

Residential PCT Ex-ante Load Impact Forecast

7.2 Forecast Methodology

The goal for this analysis is to use data from a sample of customers known to have air-conditioning to predict load impacts for the proposed PCT load control program. The analysis consists of the following steps:

- Develop an econometric model of AC load to predict AC usage for ex ante weather conditions;
- Develop a reasonable assumption for the incremental impact of PCT load control on top of a PTR rate;
- Determine the best targeting strategy using whole-building data that will be available for the whole population of potential customers. This is done by testing various targeting strategies to see which one accurately identifies customers with the highest predicted AC usage from the first step; and

Apply the assumed load impacts to the calculated reference loads on ex ante weather days for the group of customers selected by the best targeting strategy.

SDG&E has maintained an air-conditioner load-research sample (AC LRS) containing 371 customers that is representative of the SDG&E AC-owning residential population. The representativeness of this sample is assumed for this analysis and has not been verified by FSC. The AC LRS is used as a proxy for the entire AC-owning SDG&E population. For the AC LRS sample, both AC-usage data at an hourly level and whole-building usage data at an hourly level for all of 2009 and through September 2010 were available for analysis. Having both a set of data to use for simulated customer targeting and actual AC loads for the same customers was necessary to perform the analysis. Otherwise there would be no way to predict AC usage levels for the targeted group.

Each customer has a different usage pattern over time, and each customer's usage is likely to respond differently to changes in weather. This led us to estimate separate regressions for each AC unit in the sample, but using a common regression model in each case. For all AC units, the factors used to estimate usage patterns are weather variables interacted with time indicators. These allow the model to take into account different reactions to weather conditions at different times of day, times of the week and times of year. For example, a residential customer's energy usage might respond strongly to high temperatures on a Saturday afternoon when they are at home, while it might not respond at all on a Wednesday afternoon when they are at work.

The subscript t indicates the particular value at hour t within the whole dataset. Only non-holiday weekdays were modeled. Table 9-1 defines the variables and describes the effects they seek to identify. The regression specification was:

$$kWh_t = a + \sum_{h=1}^{24}\sum_{s=0}^{1}\sum_{w=0}^{1} b_{hsw}\, wacdh_t \cdot I_h \cdot I_s \cdot I_w + \sum_{h=1}^{24}\sum_{s=0}^{1}\sum_{w=0}^{1} c_{hsw}\, wacdh_t^2 \cdot I_h \cdot I_s \cdot I_w$$

Table 9-1
Description of AC Load Regression Variables

Variable	Description
a	Estimated constant
$b - c$	Estimated parameter coefficients
I_h	Indicator variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior and event impacts
I_s	Indicator variables for summer versus non-summer, designed to pick up seasonal effects
I_w	Indicator variables for weekend days
$wacdh$	Weighted average of the past 6 hours of cooling degree hours using a base of 70. Weights decrease 10% each hour so that most recent temperatures have the highest weight
ε_t	The error term, assumed to be mean zero and uncorrelated with any of the independent variables

Table 9-2 shows the predicted per customer AC load impacts, incremental to PTR impacts, for 1-in-2 and 1-in-10 weather conditions in SDG&E's territory, for an event period from 1 PM to 6 PM for each monthly system peak day. On a 1-in-2 August day, the average per customer impact is expected to be 0.43 kW. The highest impact occurs for a 1-in-10 September day, with a per customer impact of 0.54 kW. The months November through April are slightly more complicated to interpret. The program may only be called during the hours 1 PM to 6 PM, but California DR protocols call for winter load impacts to be calculated over the hours of 4 PM to 9 PM. Therefore, reference loads shown in Table 1-1 for these months are the average reference load for the hours from 4 PM to 6 PM, and load impacts are the projected load impacts for the same hours, but multiplied by 0.4. The factor 0.4 comes about because the program can only operate during 2/5 of the hours that the impacts must be calculated over.

Table 9-3 shows aggregate impacts for 2012-2014 based on the average values in Table 1-1 and on enrollment projections provided by SDG&E. Enrollment is projected to be 7,500 in 2012, 12,500 in 2013 and 15,000 in 2014. In 2014, on a 1-in-2 August peak day, the aggregate impact of the program is projected to reach 6.48 MW.

Table 9-2
Reference Loads and Incremental Load Impacts for PCT's Over and Above PTR Impacts (Average Customer, Monthly Peak Days)

	Average reference loads (kW)		Average load impacts (kW)	
	1-in-2	1-in-10	1-in-2	1-in-10
January	0.00	0.00	0.00	0.00
February	0.00	0.42	0.00	0.05
March	0.00	0.68	0.00	0.18
April	1.08	2.15	0.12	0.23
May	1.36	1.90	0.37	0.51
June	0.74	1.47	0.20	0.40
July	1.39	1.70	0.38	0.46
August	1.60	1.82	0.43	0.49
September	1.87	1.99	0.50	0.54
October	1.84	1.90	0.50	0.51
November	0.66	0.00	0.07	0.00
December	0.00	0.00	0.00	0.00

Table 9-3
Aggregate Load Impacts (MW)

	2012		2013		2014	
	1-in-2	1-in-10	1-in-2	1-in-10	1-in-2	1-in-10
January	0.00	0.00	0.00	0.00	0.00	0.00
February	0.00	0.34	0.00	0.57	0.00	0.69
March	0.00	1.38	0.00	2.30	0.00	2.75
April	0.87	1.74	1.45	2.90	1.74	3.48
May	2.75	3.85	4.59	6.41	5.51	7.70
June	1.50	2.98	2.50	4.96	3.00	5.95

July	2.81	3.44	4.69	5.74	5.63	6.89
August	3.24	3.69	5.40	6.14	6.48	7.37
September	3.79	4.03	6.31	6.72	7.57	8.06
October	3.73	3.85	6.21	6.41	7.45	7.70
November	0.55	0.00	0.91	0.00	1.09	0.00
December	0.00	0.00	0.00	0.00	0.00	0.00

The PCT ex-ante forecast used the weather station for coastal customers and the SDG&E Miramar weather station for inland customers. The weighted average temperatures for the August peak day in a 1 in 2 weather year and a 1 in 10 weather year are shown in Table 9-4 below.

Table 9-4
PCT Weather Forecast

Hour Ending	1-in-2 year Weighted Average Temperature (°F)	1-in-10 year Weighted Average Temperature (°F)
1	62.1	70.5
2	61.6	69.8
3	61.0	67.3
4	60.3	66.1
5	60.0	65.8
6	59.8	65.7
7	60.3	71.3
8	64.0	78.2
9	69.8	84.0
10	74.6	90.4
11	77.5	92.7
12	79.1	93.6
13	80.2	93.3
14	79.8	93.3
15	80.7	94.7
16	80.4	95.4
17	80.0	94.1
18	78.4	92.5
19	75.6	86.1
20	70.3	81.2
21	68.5	77.6
22	66.2	76.0
23	64.6	72.8
24	64.0	70.5

7.3 Residential Pool Pump Forecast

Hourly load impacts per customer for the pool pumps were taken from Table 21 page 31 of the Pool Pump Demand Response Potential Study. This study was prepared by the design and engineering services customer service business unit at SCE and published in June of 2008. In the study end-use metering was installed on customer pool pumps and the hourly pool pump energy use was measured. The forecast assumes that pool pump load impacts do not change with weather.

8. PLS Pilot Program Overview

The Permanent Load Shift Program (PLS) is designed as a permanent peak load reduction program. The phrase “permanent load shift” refers to the shifting of energy usage by one or more customers from one-time period-to another on a recurring basis, and for this program, refers to shifting load during the “peak hours” (11am-6pm) within the “peak period”(May -October) of the year. The program is not part of the energy efficiency initiative. Although the program is not a demand response program for regulatory purposes it is often included in demand response proceedings.

The PLS pilot resulted from a 2008 CPUC decision (D.06-11.049) directing the CA IOU’s to seek Permanent Peak Load Reduction in their service territories. SDG&E was authorized to shift up to $4,000,000 of its 2006-2008 DR budget to fund PLS, and to pursue an RFP process to seek proposals. The SDG&E RFP process resulted in two contracts for the PLS program effective through 2011. For 2012-2014 SDG&E proposed in application a PLS program that will focus on two technology types: Thermal Storage and Non-Thermal Storage. An example of thermal storage is making ice or chilled water at night to provide cooling during the day thereby reducing the on-peak air conditioning load. Non-thermal storage includes chemical batteries that are charged with electricity during the night and discharged during on-peak hours. SDG&E's proposes providing a standard capacity offer of $500/kW, target contractors who will work with customers to implement the selected technologies and to ensure systems are properly designed, properly built and commissioned and properly operated. Decision 12-040-45 approved the PLS program for 2012-2014 but directed SDG&E, SCE and PG&E to standardize their proposed PLs programs and to submit and to file an updated PLS proposal with updated cost-effectiveness tests by August 1st 2012.

8.2 PLS Evaluation methodology

Measurement and evaluation of the PLS pilot was done using engineering measurement and evaluation methods. PLS is a non-event based resource since the load shift is permanent and there are no events called. The non-event based section of the load impact protocols states "Engineering analysis is another approach that might be suitable for some resource options that are largely technology driven and that have much more limited behavioral variation than do pricing resources, for example. Permanent load shifting options such as ice storage and energy management systems are examples where engineering analysis may be suitable for estimating load impacts.

Three customers participated in the PLS program. Two converted to chillers powered by gas and two installed refrigerated zone control technologies According to engineering analysis these customers achieved a load reduction of 2336 kW. Since two of the customers did convert to gas cooling it is reasonable to assume these customers load reduction will be weather sensitive. However, the engineering estimate does not provide weather adjusted impacts. Therefore a regression model based on the reference load data was used to create weather adjusted impacts. The regression model used variables of day of week, month and average daily temperature to estimate the reference load. Once a reference load was estimated for each monthly weather scenario the differences in these reference loads by month were used to adjust the engineering estimates for weather. For example the 2012 reference load forecast for May was 395 kW less than the reference load for September so the demand response estimate for May is 395 kW less than then September estimate. The September estimate is set to the engineering estimate since the September weather represents peak conditions. Athough the technology installed in permanent SDG&E commercial customer face a high rate between 11a.m to 6p.m only in the months of May through September. For the other months the peak period changes to 5pm-8pm. Therefore program impacts are shown for May-Septbemr when the time of use rate is in place from 11a.m to 6 p.m. The pilot achieved a total of 2.4 MW of load reduction between 2001 and 2011 and SDG&E forecast that the program will continue to grow up to 5.05 MW by 2014.

1-in-2 Year Weather Conditions Permanent Load Shifting Load Impacts

	Month and Resource Adequacy Window											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	1 - 6 PM											
2012	-	-	-	-	1.94	1.84	2.26	2.28	2.34	-	-	-
2013	-	-	-	-	3.15	2.98	3.66	3.70	3.78	-	-	-
2014	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2015	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2016	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2017	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2018	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2019	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2020	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-
2021	-	-	-	-	4.34	4.11	5.05	5.11	5.22	-	-	-

9. Portfoio

Customers can participate in both the CPP-D rate and BIP, the CPP-D rate and CBP DO. Since CPP-D was classified as an energy program in D.12-04-045 when there is dual participation between CPP-D and another program the load impacts must be subtracted from the CPP-D results. The forecasted number of bundled customer forecasted to be enrolled either BIP or CBP DO along with CPP-D had to be subtracted from the CPP-D enrollment forecast.

Another area of multiple program participation involves PTR and SCTD. The PTR forecast assumes no enabling technology and the SCTD forecast includes the incremental affect of technology above PTR so there is no double counting between thee programs.