Executive Summary of the 2009 SDG&E Measurement and Evaluation Load Impact Reports

April 22, 2010

SDGE

A Sempra Energy utility℠

Table of Contents

1 SDG&E's 2009 Load Impact Executive Summary

In Decision 08-04-050 the commission required 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 joint utilities filed a petition to modify the decision D.08-41-50 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 Decision 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 by April 22nd 2010. The Decision stated that executive summary must include summaries of each load impact report along with 44 summary tables that include the forecasted load reductions for all demand response activities.

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), and the Summer Saver program. The base interruptible program (BIP) and critical peak pricing emergency (CPP-E) programs were active in 2009, but no events were called. Therefore a summary of the ex-ante forecasts is provided for these programs. There are two new commission approved demand response activities included in this report. The aggregator managed portfolio program will begin in 2010 and the peak time rebate program will begin in 2011. 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 11-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 appendix A of this report.

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 and Electric (SDG&E), for Program Year 2009. 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

SDG&E's CBP DA was called 6 times and the CBP DO was called 7 times. Estimated *ex post* load impacts on an average hourly basis for the average event for the SDG&E CBP DA was 10.3 MW and the ex-post impact for the average event was 12.5 MW for the CBP DO program. There were 131 meters that were nominated during 2009 in the CBP DA program and 300 meters that were nominated in 2009 in the CBP DO program. Tables 2-1 and 2-2 below show the average load reduction for each CBP DA and CBP DO event.

Table 2-1

Average Hourly Load Impacts (kW) by Event -- *SDG&E CBP DA*

Event	Date	Day of Week	SAIDs Called	Estimated Reference Load (kW)	Observed Load (kW)	Estimated Load Impact (kW)	% LI
1	July 21, 2009	Tuesday					
2	August 26, 2009	Wednesday					
3	August 27, 2009	Thursday	113	38,814	28,224	10,590	27%
4	August 28, 2009	Friday	113	38,492	28,322	10,170	26%
5	September 2, 2009	Wednesday					
6	September 3, 2009	Thursday	127	41,124	29,486	11,638	28%
7	September 4, 2009	Friday	127	37,606	28,424	9,182	24%
8	September 24, 2009	Thursday	127	40,065	30,412	9,653	24%
9	September 25, 2009	Friday	127	38,055	27,761	10,295	27%
	Average		122	39,026	28,771	10,255	26%
	Standard Deviation			1,324	985	842	2%

Table 2-2

Average Hourly Load Impacts (kW) by Event -- *SDG&E CBP DO*

Event	Date	Day of Week	SAIDs Called	Estimated Reference Load (kW)	Observed Load (kW)	Estimated Load Impact (kW)	% LI
1	July 21, 2009	Tuesday	265	62,728	52,417	10,311	16%
2	August 26, 2009	Wednesday	272	70,359	55,151	15,209	22%
3	August 27, 2009	Thursday	272	69,719	55,786	13,934	20%
4	August 28, 2009	Friday	272	68,769	57,140	11,630	17%
5	September 2, 2009	Wednesday	283	72,707	60,594	12,113	17%
6	September 3, 2009	Thursday	283	75,623	60,131	15,492	20%
7	September 4, 2009	Friday					
8	September 24, 2009	Thursday	283	68,114	59,308	8,805	13%
9	September 25, 2009	Friday					
	Average		276	69,717	57,218	12,499	18%
	Standard Deviation			4,011	2,990	2,506	3%

2.3 CBP Evaluation Methodology

Estimates of total program-level load impacts for each program were developed from the coefficients of individual customer regression equations. These equations were estimated over the summer months for 2009, using individual customer load data for all customer accounts enrolled in each program.

The regression equations were based on models of hourly loads as functions of a list of variables designed to control for factors such as:

- Seasonal and hourly time patterns (*e.g.*, month, day-of-week, and hour, plus various hour/day-type interactions)
- Weather (*e.g.*, cooling degree hours)
- Event indicators—Event indicators, which were invoked when a given customer's program type was called, were interacted with hourly indicator variables to allow estimation of hourly load impacts for each event.

The resulting equations provide the capability of measuring hourly load impacts on event days, as well as simulating hourly reference load profiles for various day-types and weather conditions. In addition, the customer-specific equations provide the capability to summarize load impacts by industry type. Finally, uncertainty-adjusted load impacts were calculated to illustrate the degree of uncertainty that exists around the estimated load impacts

Ex post load impacts were estimated using customer-level hourly data from May through October. The primary regression model is characterized as follows:

$$
\begin{aligned}
Q_t \; &= a + \sum_{Evt=1}^{E} \sum_{i=1}^{24} (b_{i,Evt}^{AGG} \times h_{i,t} \times AGG_t) + b^{MornLoad} \times MornLoad_t + \sum_{i=1}^{24} (b_i^{CDH} \times h_{i,t} \times CDH_t) \\
&+ \sum_{i=2}^{24} (b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24} (b_i^{FRI} \times h_{i,t} \times FRI_t) + \sum_{i=2}^{24} (b_i^{h} \times h_{i,t}) + \sum_{i=2}^{5} (b_i^{DTYPE} \times DTYPE_{i,t}) \\
&+ \sum_{i=6}^{10} (b_i^{MONTH} \times MONTH_{i,t}) + b_t^{Summer} \times Summer_t + \sum_{i=1}^{24} (b_i^{CDH,S} \times h_{i,t} \times Summer_t \times CDH_t) \\
&+ \sum_{i=2}^{24} (b_i^{MON,S} \times h_{i,t} \times Summer_t \times MON_t) + \sum_{i=2}^{24} (b_i^{FRI,S} \times h_{i,t} \times Summer_t \times FRI_t) \\
&+ \sum_{i=2}^{24} (b_i^{h,S} \times h_{i,t} \times Summer_t) + e_t
\end{aligned}
$$

In this equation, Q_t represents the demand in hour t for a customer nominated in the month of the event date; the b's are estimated parameters; $h_{i,t}$ is a dummy variable for hour i; AGG_t is an indicator variable for program event days; CDH_t is cooling degree hours;[1] E is the number of event days that occurred during the program year; $MornLoad_t$ is a variable equal to the average of the day's load in hours 1 through 10; MON_t is a

[1] Cooling degree hours (CDH) was defined as MAX[0, Temperature – 50], where Temperature is the hourly temperature in degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station.

dummy variable for Monday; FRI_t is a dummy variable for Friday; $DTYPE_{i,t}$ is a series of dummy variables for each day of the week; $MONTH_{i,t}$ is a series of dummy variables for each month; $Summer_t$ is a variable defining summer months (defined as mid-June through mid-August)[2], which is interacted with the weather and hourly profile variables; and e_t is the error term. The "morning load" variable was used in lieu of a more formal autoregressive structure in order to adjust the model to account for load levels on a particular day, particularly for customers whose daily loads vary substantially for no observable reason (such as more or less intensive than average operations on the part of manufacturing customers). Because of the autoregressive nature of the morning load variable, no further correction for serial correlation was performed in these models.

Separate models were estimated for each customer. The estimated load impacts, in the form of hourly event coefficients, were aggregated across customers to arrive at program-level load impacts, and results by industry group and LCA. Overall program-level and aggregator-level regressions were also estimated in some cases, primarily to provide consistency checks for the individual customer results.

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 2010 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.

The forecasts of load impacts were developed in two primary stages. First, estimates of reference loads and percentage load impacts, on a per-enrolled customer basis, were developed based on modified versions of the ex-post load impact regressions described in Section 4. Second, the simulated per-customer reference loads under alternative weather (*e.g.*, 1-in-2 and 1-in-10) and event-type scenarios (*e.g.*, typical event,

[2] This variable was initially designed to reflect the load changes that occur when schools are out of session. We have found the variable to be a useful part of the base specification, as it helps somewhat in modeling schools and does not appear to harm load impact estimates even in cases in which the customer does not change its usage level or profile substantially during the summer months.

or monthly system peak day), and the estimated percentage load impacts were combined with program enrollment forecasts from the utilities to develop alternative forecasts of aggregate load impacts. Forecasts were developed at the program and program-type (*e.g.*, DA and DO) level.

The ex-ante regression equations are similar in design to the ex post load impact equations, differing primarily in two ways. First, the event variables are modified from the version that produced ex-post estimates of 24 hourly load impact values for *each* event, to a version that produces estimates of *average hourly event-period* load impacts across all events.[3] Second, the ex ante models exclude the morning-usage variable. While this variable is useful for improving accuracy in estimating ex post load impacts for each event, it complicates the use of the equations in ex ante simulation. That is, it would require a separate simulation of the level of the morning load. The regression equations contain both weather variables and monthly indicator variables, which provide the capability to simulate customer loads under the different weather and monthly system peak scenarios.

For SDG&E's CBP program, we developed per-customer load profiles by industry group and program type (*e.g.*, combinations of notice level and event window), after removing the customer accounts for the aggregator that will offer the new AMP DO product. 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 for the CBP program is largely based on the historical growth of the program. The tables below shows historical number of customers nominated and the average load impact for year for 2007-2009 and SDG7E's enrollment forecast for 2010-2014. Enrollment after 2014 is forecasted as constant. Table 2-3 shows that from 2007-2009 the CBP DA grew at a slower pace than the CBP DO and therefore a modest growth rate was predicted for 2010-2014 for this option. The CBP day-of option on the other hand has grown rapidly, more than doubling in size form 2007 to 2008 and form 2008 to 2009. From 2009 to 2010 there is very little growth overall for

[3] The equations also estimated load impacts for the hours immediately preceding and following an event (since many customers begin reducing load prior to an event and do not immediately increase load following an event), and for all remaining event-day hours.

hits option because the forecast predicts that one aggregator will more their CBP DO customers to their new contract, but that other aggregators will continue to enroll customers on the CBP DO leading to approximately zero growth from 2009 to 2010. After 2010 however the growth CBP DO option is expected to continue to grow although at lower levels than the growth rates from 2007 to 2009.

Table 2-3

CBP Historical data and Enrollment Forecast				
year	Customers DA	Customers DO	MW DA	MW DO
2007	55	35	6.6	1.2
2008	96	137	10.3	6.2
2009	131	300	10.3	12.5
2010	136	339	n/a	n/a
2011	144	418	n/a	n/a
2012	153	495	n/a	n/a
2013	159	547	n/a	n/a
2014	165	593	n/a	n/a

The CBP ex-ante forecast used weather data from SDG&E Lindberg Field 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 2-4 below.

Table 2-4

Hour Ending	1 in 2 year Weighted Average Temperature (°F)	1 in 10 year weighted average temperature (F)
1	72	73
2	70	73
3	69	72
4	70	72
5	69	72
6	69	72
7	70	71
8	69	74
9	74	77
10	76	82
11	81	83
12	83	87
13	83	83
14	82	82
15	82	83
16	80	84
17	81	83
18	79	82
19	75	80
20	73	77
21	72	76
22	72	76
23	72	74
24	71	74

3 Summary of SDG&E's CPP-D Report

3.1 CPP-D Rate Description

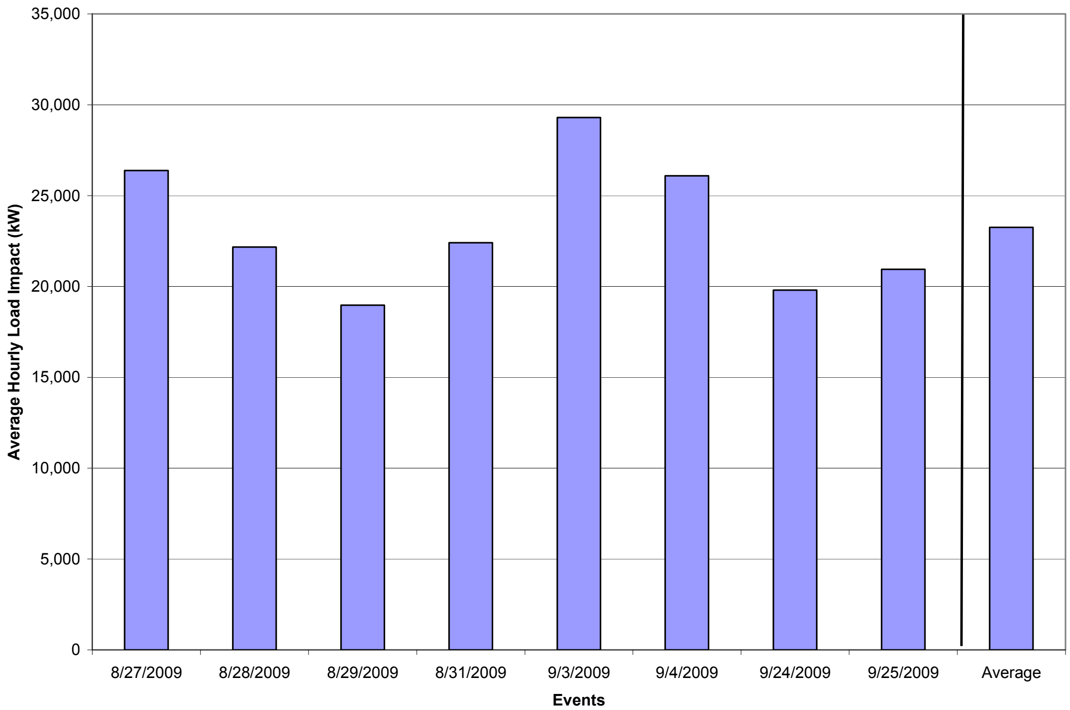
This report documents the results of a *load impact evaluation* for program-year 2009 of the SDG&E CPP-D rate. The primary goals of the evaluation were to estimate the hourly ex-post load impacts achieved on each event day and to provide ex-ante forecasts of the load impacts expected to be achieved by CPP-D for 2010-2020. Beginning in May 2008, SDG&E implemented CPP-D with an "opt-out" provision, 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 guarantee for one 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

In 2009 1580 customer were enrolled in CPP-D. SDG&E called eight events in 2009. One event occurred on Saturday August 29th. The average load reduction for weekday CPP-D events was 23.3 MW which was a 5.6% load reduction. The average load reduction on the peak day September 3rd was 29 MW, and the average load reduction on the Saturday event was 19 MW. The load impacts for the remaining events are shown in Figure 3-1 below.

Figure 3-1
Average Hourly CPP Load Impacts by Event – *SDG&E*



The methodology of estimating customer-specific regression equations and load impacts in this evaluation also provides the capability to examine the distributions of CPP load impacts across customer accounts. In SDG&E 35% of customers had an estimated response of more than 5 kW, and 4.6% of the customers provided 72% of the total load reduction.

3.3 CPP-D Methodology

The CPP ex post hourly load impacts for program-year 2009 were estimated using separate econometric models (*i.e.*, regression equations) for each enrolled CPP customer, based on historical customer load data for the summer of 2009. The models assume that customers' hourly loads are functions of weather data, time-based variables such as hour, day of week, and month, and program event information (*e.g.*, the days and hours in which events were called). The individual customer models allow the development of information on the distribution of load impacts across industry types and on the distribution of the impacts of the load impacts across customers.

The model that was used for the PG&E and SCE customers is shown below.

$$Q_t = a + \sum_{Evt=1}^{E} \sum_{i=1}^{24}(b_{i,Evt}^{CPP} \times h_{i,t} \times CPP_t) + b^{MornLoad} \times MornLoad_t + \sum_{i=1}^{24}(b_i^{CDH} \times h_{i,t} \times CDH_t)$$
$$+ \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) + \sum_{i=2}^{24}(b_i^{h} \times h_{i,t}) + \sum_{i=2}^{5}(b_i^{DTYPE} \times DTYPE_{i,t})$$
$$+ \sum_{i=6}^{10}(b_i^{MONTH} \times MONTH_{i,t}) + b_t^{Summer} \times Summer_t + \sum_{i=1}^{24}(b_i^{CDH,S} \times h_{i,t} \times Summer_t \times CDH_t)$$
$$+ \sum_{i=2}^{24}(b_i^{MON,S} \times h_{i,t} \times Summer_t \times MON_t) + \sum_{i=2}^{24}(b_i^{FRI,S} \times h_{i,t} \times Summer_t \times FRI_t)$$
$$+ \sum_{i=2}^{24}(b_i^{h,S} \times h_{i,t} \times Summer_t) + b^{OTH} \times OTH_t + e_t$$

In this equation, Q_t represents the amount of usage in hour t for a customer enrolled in CPP prior to the last event date; the b's are estimated parameters; $h_{i,t}$ is a dummy variable for hour i; CPP_t is an indicator variable for program event days; CDH_t is cooling degree hours;[4] E is the number of event days that occurred during the program year; $MornLoad_t$ is a variable equal to the average of the day's load in hours 1 through 10; MON_t is a dummy variable for Monday; FRI_t is a dummy variable for Friday; $DTYPE_{i,t}$ is a series of dummy variables for each day of the week; $MONTH_{i,t}$ is a series of dummy variables for each month; $Summer_t$ is a variable indicating summer months (defined as mid-June through mid-August)[5], which is interacted with the weather and hourly profile variables; OTH_t is a dummy variable indicating an event hour for a non-CPP demand response program in which the customer is also enrolled; and e_t is the error

[4] Cooling degree hours (CDH) was defined as MAX[0, Temperature – 50], where Temperature is the hourly temperature in degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station. Our previous studies used cooling degree days with a 65 degree threshold (CDD65). Our review of the results this year found that using CDH50 in place of CDD65 produced implied event-day reference loads that better reflected observed usage patterns and levels on hot, non-event days.

[5] This variable was initially designed to reflect the load changes that occur when schools are out of session. We have found the variables to a useful part of the base specification, as they do not appear to harm load impact estimates even in cases in which the customer does not change its usage level or profile during the summer months.

term. The “morning load” variable was used in lieu of a more formal autoregressive structure in order to adjust the model to account for the level of load on a particular day. Because of the autoregressive nature of the morning load variable, no further correction for serial correlation was performed in these models.

For SDG&E, initial regression results suggested that the equations were not adequately capturing mid-day weather effects on the hottest days of the summer, which were also SDG&E CPP event days. We therefore added two sets of 24 variables in which hour dummies (for the summer and non-summer periods) were interacted with the *square* of cooling degree hours.

3.4 CPP-D Ex Ante Load Impacts

Ex-ante CPP-D load impacts for existing CPP-D customers were prepared for 2010-2020 based on per-customer reference loads and load impact estimates from the ex post evaluation, and enrollment forecasts. The enrollment forecast for CPP-D was calculated using opt-out rates by North American Industrial Classification System (NAICS) calculated by Freeman Sullivan & Company (FSC). The historical data for 2008 and 2009 contained both customers who enrolled in CPP-D in 2008 and customers who enrolled in CPP-D in 2009, and therefore enabled an analysis of opt-out rates in both the first year and the second year of a CPP-D rate. The overall percentage of customers forecasted to remain on CPP-D for 1 year is 74.5%. Of customers who remained on default CPP-D for one year 877.8% are forecasted to remain on CPP-D for a second year. Table 3-1 below shows the results broken out by NAICS group. These percentages were applied to the first two years of enrollment for CPP-D customers, opt-out rates in the third year were predicted to be 2% lower than they were for the second year and enrollment for CPP-D was forecasted to remain constant. The ex-ante forecast tables for the CPP-D rate are provided in Appendix A.

Table 3-1

Percentage of customers remaining on CPP-D

Naics code Group	Probability of CPP-D first year	Probability of CPP-D second year (out of CPP-D customers enrolled first year)
Agriculture, Mining & Construction	59.2%	78.5%
Manufacturing	74.6%	91.0%
Wholesale, Transport, other utilities	81.1%	96.4%
Retail stores	74.9%	90.3%
Offices, Hotels, Finance, Services	73.0%	87.0%
Schools	72.1%	81.9%
Institutional/Government	74.5%	92.2%
TOTAL	74.5%	88.7%

3.4.1 Ex-Ante Summary Medium Commercial CPP-D

Beginning in May 2008, SDG&E implemented CPP-D with an "opt-out" provision, and began transitioning previous volunteers onto the new default rate. All customers with an interval data meter that were not participating in another demand response program were defaulted to the CPP-D rate. Although some customers with an on-peak demand of less than 200 kW have interval meters and were defaulted onto CPP-D the majority of customers with an on-peak demand of less than 200 kW so not have interval meters yet. These customers that have not yet been defaulted are referred to as medium commercial customers in the CPP-D this report. The medium commercial CPP-D rate is the same as the large commercial CPP-D rate.

The ex-ante analysis of the medium commercial CPP-D customers requires a forecast of the reference loads, an estimate of the percentage load impacts, an enrollment forecast, and assumption about meter deployment rates. Reference load forecasts were based on 2009 daily load profile data provided by SDG&E and adjusted for each temperature scenario using regression models by Christensen consulting. The percent load impacts for the medium commercial CPP-D customers were calculated by applying the elasticities from the Statewide Pricing Pilot study to the current CPP-D rates.

The enrollment forecast for medium commercial CPP-D used the FSC analysis of the characteristics of CPP-D opt out customers to predict the number of medium commercial CPP-D customer who will remain on the CPP-D rate. The FSC forecast model was broken down by NAICS group and also used many indicators of load shape to predict the percentage of customers remaining on the CPP-D program. Variables in the model included the average annual consumption, the percentage of annual load that is not summer on-peak usage, the average summer demand during the summer on-peak period, average summer peak to off-peak ratio and the maximum summer on-peak demand. The medium commercial customers were broken down into NAICS code group and their load data was entered into the FSC model. The model predicted that 77% of medium commercial customers would remain on the CPP-D rate the first year and that 89% of the customers who remained on the CPP-D rate the first year would remain on the CPP-D rate the second year. These opt-out rates were very similar to the opt-out rates for the large CPP-D customers. More detailed opt-out rates by NAICS code group are provided below.

Table 3-2

Percentage of Medium Commercial CPP-D customers remaining on CPP-D

Naics Code Group	Probability of CPP-D first year	Probability of CPP-D 2nd year (out of customers enrolled 1 year)
Agriculture, Mining & Construction	73.1%	85.4%
Manufacturing	75.0%	87.0%
Wholesale, Transport, other utilities	85.6%	97.6%
Retail stores	78.1%	89.4%
Offices, Hotels, Finance, Services	77.2%	88.7%
Schools	69.2%	79.2%
Institutional/Government	74.8%	86.8%
TOTAL	77.0%	89.2%

The enrollment forecast for medium commercial CPP-D customers also depends on the meter deployment rates. The medium CPP-D default is scheduled to begin in 2013 because in January of 2013 the meter deployment forecast predicts that 47% of medium commercial customers will have smart meters installed, tested and verified, that 71.4% of medium commercial customers will have smart meters installed, tested and verified and that 100% of medium commercial customers will have smart meters installed, tested and verified by November of 2013.

4 Summary of SDG&E's Summer Saver Report

4.1 Summer Saver Program Description

San Diego Gas and 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. This report provides ex post load impact estimates for the Summer Saver program for 2009 and ex ante load impact forecasts for 2010 through 2020.

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.

As of early 2010, there were 29,527 premises enrolled in the program, which in aggregate have roughly 144,000 tons of air conditioning capacity. Almost 82% of participants were residential customers, although these customers accounted for approximately two thirds of the total tons of cooling that are subject to control under the program. Roughly 48% of residential participants elected the 100 percent cycling option and about one quarter or residential customers chose to allow cycling on both week days and weekends. Almost 60% of commercial customers selected the 50% cycling option over the 30% option, but less than 5% of commercial customers chose to allow cycling on the weekend.

Summer Saver enrollment is expected to increase to roughly 169,000 tons of air conditioning by the end of 2011, a growth of about 17%, and then remain constant from 2012 through 2020. Enrolled capacity is expected to grow faster in the residential sector (19%) compared with the commercial sector (13%). The average load reduction will increase over this period as a result of the much greater forecasted enrollment in the residential 100% cycling option (35% growth) compared with the 50% cycling option (3%). Growth in the commercial 50% cycling option (15% growth) is also expected to be greater than growth in the 30% cycling option (11%).

4.2 Summer Saver Ex Post Load Impact Estimates

Seven Summer Saver events were called in 2009 and all residential and commercial accounts were called for each event. All called events were four hours long and each one began either at 1 pm, 1:30 pm or 2 pm. The first event was called on July 21st. There were three events each in August and September, with the last event on September 24th. The August events were called three days in a row, and two of the three September events were on back-to-back days.

Tables 4-1 through 4-3 show the load impacts for each event day for residential customers, commercial customers and all customers combined, respectively. The enrollment values are reported in terms of tons of air conditioning, and the average reference loads and load impacts are in terms of kW/ton of air conditioning. In total, the Summer Saver program delivered an average load reduction across the four-hour event window and the seven events equal to 23.6 MW. The impacts ranged from a low of 17.4

MW on July 21st to a high of 27.7 MW on August 27th. The percent load reduction also varied across events, from a low of 35% on July 21st to a high of 46% on August 28th. Residential customers accounted for almost two thirds of the enrolled tonnage of air conditioning and almost three quarters of the total load reduction. The average load reduction for residential and commercial customers is quite similar, 0.18 kW/ton and 0.14 kW/ton, respectively. The percent load reduction is much higher for residential customers compared with commercial customers, due in large part to the different cycling options offered to the two segments. Residential customers are split about 50/50 between 50% and 100% cycling, while commercial customers are split 60/40 between 50% and 20% cycling.

Table 4-1
2009 Average Hourly Load Reduction for Event Period by Event Day
All Residential Summer Saver Customers, kW per Ton of Air Conditioning

Date	Day of Week	Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	92,006	0.25	0.11	0.14	55.9	12.8	85.3
8/26/2009	W	96,223	0.27	0.10	0.18	64.1	16.9	90.6
8/27/2009	Th	96,217	0.38	0.17	0.21	54.9	20.2	92.9
8/28/2009	F	96,223	0.32	0.11	0.21	65.7	19.9	92.5
9/2/2009	W	96,214	0.38	0.21	0.17	45.4	16.5	86.4
9/3/2009	Th	96,220	0.37	0.17	0.19	53.0	18.6	88.3
9/24/2009	Th	96,727	0.32	0.16	0.16	51.2	15.9	90.2
Average Event	**N/A**	**95,690**	**0.33**	**0.15**	**0.18**	**55.3**	**17.3**	**89.5**

Table 4-2
2009 Average Hourly Load Reduction for Event Period by Event Day
All Commercial Summer Saver Customers, kW per Ton

Date	Day of Week	Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	48,098	0.51	0.41	0.10	19.9	4.9	83.0
8/26/2009	W	48,808	0.53	0.40	0.13	24.8	6.5	87.9
8/27/2009	Th	48,817	0.59	0.43	0.16	27.4	7.9	90.2
8/28/2009	F	48,808	0.56	0.40	0.16	28.1	7.6	89.6
9/2/2009	W	48,817	0.56	0.43	0.13	23.7	6.5	84.8
9/3/2009	Th	48,808	0.53	0.38	0.15	28.6	7.4	86.8
9/24/2009	Th	47,142	0.57	0.45	0.12	20.7	5.6	87.6
Average Event	**N/A**	**48,471**	**0.55**	**0.41**	**0.14**	**24.8**	**6.6**	**87.1**

Table 4-3
2009 Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Customers, kW per Ton

Date	Day of Week	Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	140,104	0.35	0.23	0.12	35.1	17.4	84.5
8/26/2009	W	145,030	0.37	0.21	0.16	42.7	23.1	89.7
8/27/2009	Th	145,033	0.46	0.27	0.19	41.2	27.7	92.0
8/28/2009	F	145,030	0.41	0.22	0.19	46.2	27.3	91.5
9/2/2009	W	145,030	0.45	0.29	0.16	34.8	22.8	85.8
9/3/2009	Th	145,027	0.43	0.25	0.18	41.6	25.7	87.8
9/24/2009	Th	143,869	0.42	0.27	0.15	35.3	21.1	89.4
Average Event	**N/A**	**144,161**	**0.41**	**0.25**	**0.16**	**39.6**	**23.6**	**88.7**

There is a clear selection bias found among participants, with customers that have larger average energy use for air conditioning more likely to select the lower cycling option among the two offered. For example, the average reference load during the event period for residential customers on the 50% cycling option is roughly one third larger than for those on the 100% cycling option. For commercial customers, those who chose the 30% cycling option have reference loads that are almost 65% greater than those on the 50% cycling option.

In part because of the selection bias, the difference in average load impacts provided by the different customer segments is not as great as the difference in cycling strategies used. Put another way, while the percent reduction for the 50% cycling residential group is roughly half that of the 100% cycling group, the 50% cycling group provides absolute load reductions that are only 20% less than those provided by the 100% cycling group. In light of this, and the fact that the residential 100% cycling group is paid four times as much to participate as is the 50% cycling group, it may be possible to improve program cost effectiveness by increasing the share of program participants on the lower cost 50% cycling option and/or by reducing the incentive paid for 100% cycling while increasing the incentive paid for 50% cycling.

4.3 Summer Saver Methodology

The impact estimates for commercial and residential customers were based on end use data. Models with whole building data and whole house data respectively were also estimated for comparison purposes. In total, 420 accounts were selected from SDG&E's full commercial participant population and 279 accounts were selected from the full residential participant population for the 2009 Summer Saver program evaluation. The final commercial estimation was based on 250 individual air conditioning unit regressions[6] and the final residential estimation as based on 276 individual air conditioning units[7].

The commercial sampled customers were divided into three groups so that each event day had a comparison group that was not called and two curtailed groups that were called. Of the 250 customers in the final estimating sample, 75 were in group A, 62 in group B, and 113 in group C. Groups A and B alternated between the curtailed and comparison groups from one event to the next. Group C was always in the curtailed group.

---

[6] Thirteen customers were dropped due to lack of corresponding customer characteristic data or an excessive number of large spikes observed in the customer's load data. 157 accounts were dropped due to discovery of an error in the data associated with the end use data loggers. This error was discovered on March 29th, which did not leave enough time to incorporate those accounts into the analysis.

[7] Three customers were dropped due to an excessive number of spikes observed in the customer's load data.

The residential sampled customers were divided into two groups so that each event day had a comparison group that was not called and a curtailed group that was called. Of the 276 customers in the final estimating sample, 139 were in group A and 137 were in group B. Groups A and B alternated between the curtailed and comparison group from one event to the next.

The commercial and residential regressions were developed using a GLS estimator with robust standard errors. The following equations summarize the specification models used to estimate air condition load based on end use load data:

Commercial:

$$KW_{in} = \alpha_0 + \sum_{i=1}^{48}\sum_{j=5}^{9} \beta_{ij} \cdot HALFHOUR_i \cdot MONTH_j + \sum_{i=1}^{48}\sum_{k=1}^{5} \delta_{ik} \cdot HALFHOUR_i \cdot DAYTYPE_k +$$

$$\sum_{i=1}^{48}\sum_{k=1}^{5} \mu_{ik} \cdot HALFHOUR_i \cdot DAYTYPE_k \cdot CDD + \sum_{i=1}^{48}\sum_{k=1}^{5} \eta_{ik} \cdot HALFHOUR_i \cdot DAYTYPE_k \cdot CDD^2 +$$

$$\sum_{l=1}^{8} \pi_l \cdot EVENTHALFHOUR_l \cdot CDD + \sum_{m=1}^{12} \theta_m \cdot POSTEVENTHOUR_m \cdot sumCDH + \varepsilon$$

In this equation,

KW = Half hourly air conditioning load in half-hour i for customer n;

α_o = Estimated constant term;

β_{ij} through θ_m are the estimated coefficients;

$HALFHOUR_i$ = Series of binary variables representing each half-hour of the day (1-48);

$MONTH_j$ = Series of binary variables representing each summer month (5-9);

$DAYTYPE_j$ = Series of binary variables representing each day type (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday);

CDD = Cooling degree days for that day (base 65° F)

CDD^2 = CDD squared

$EVENTHALFHOUR_l$= Series of binary variables representing each half-hour of the event window (1-8; events were four hours long);

$POSTEVENTHOUR_m$= Series of binary variables representing twelve half-hour time periods immediately following the end of an event (1-12);

sumCDH = Cumulative cooling degree hours (base 70° F) during the event period, and;

ε = the error term.

Residential:

$$KW_{in} = \alpha_0 + \sum_{i=1}^{48}\sum_{k=1}^{2} \delta_{ik} \cdot HALFHOUR_i \cdot DAYTYPE_k \cdot CDD +$$
$$\sum_{i=1}^{48}\sum_{k=1}^{2} \delta_{ik} \cdot HALFHOUR_i \cdot DAYTYPE_k \cdot CDDsqr +$$
$$\sum_{i=1}^{48}\sum_{j=5}^{9} \beta_{ij} \cdot HALFHOUR_i \cdot MONTH_j \cdot CDD +$$
$$\sum_{i=1}^{48}\sum_{j=5}^{9} \beta_{ij} \cdot HALFHOUR_i \cdot MONTH_j \cdot CDDsqr +$$
$$\sum_{i=1}^{48}\mu_i \cdot HALFHOUR_i \cdot NIGHTCDH + \sum_{l=1}^{8}\pi_l \cdot EVENTHALFHOUR_l \cdot CDD +$$
$$\sum_{m=1}^{12} \theta_m \cdot POSTEVENTHOUR_m \cdot sumCDH + \varepsilon$$

In this equation,

KW = Half hourly air conditioning load in half-hour i for customer n;

α_o = Estimated constant term;

β_{ij} through θ_m are the estimated coefficients;

$HALFHOUR_i$ = Series of binary variables representing each half-hour of the day (1-48);

$MONTH_j$ = Series of binary variables representing each summer month (5-9);

$DAYTYPE_j$ = Series of binary variables representing each day type (Weekday, Weekend/Holdiay);

CDD = Cooling degree days for that day (base 65° F)

CDD^2 = CDD squared

NIGHTCDH= Cumulative cooling degree hours (base 70° F) from 12 am to 6 am;

$EVENTHALFHOUR_l$= Series of binary variables representing each half-hour of the event window (1-8; events were four hours long);

$POSTEVENTHOUR_m$= Series of binary variables representing twelve half-hour time periods immediately following the end of an event (1-12);

sumCDH = Cumulative cooling degree hours (base 70° F) during the event period, and;

ε = the error term.

4.4 Ex Ante Summer Saver Load Impact Estimates

The models developed from the ex post load data in 2009 were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2010 through 2020. 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 and a typical event day.[8] SDG&E also provided enrollment estimates by customer type and cycling option, which are presented in Table 4-4. The program is forecasted to reach a steady state by the end of 2011. As such, the last year in which load impact estimates change is 2012. Ex ante estimates for 2013 through 2020 are the same as for 2012. The ex ante event window chosen by SDG&E is from 1 to 6 pm.[9]

Table 4-4 shows the expected increase in enrollment in the Summer Saver program through the end of 2011. Summer Saver enrollment is expected to increase to roughly 169,000 tons of air conditioning by the end of 2011, a growth of about 17%, and then remain constant from 2012 through 2020. Enrolled capacity is expected to grow faster in the residential sector (19%) compared with the commercial sector (13%). The average load reduction will increase over this period as a result of the much greater forecasted enrollment in the residential 100% cycling option (35% growth) compared with the 50% cycling option (3%). Growth in the commercial 50% cycling option (15% growth) is also expected to be greater than growth in the 30% cycling option (11%). The enrollment forecast begins with the tons enrolled as of February 2010 for each customer type and cycling option then predicts that the monthly growth rates thought April 2011 will be equal to 70% of the historical average monthly growth rate from February 2009 to February 2010. Form April 2011 to December 2011 the predicted growth rate is 35% of the historical monthly growth rate.

---

[8] SDG&E selected weather data to represent the 1-in-2 and 1-in-10 year conditions based on an analysis of data from two key weather stations, Miramar and Lindbergh for the period from 2003 through 2009, The median value for each month was selected to represent 1-in-2 year weather and the second highest value for each month was used to represent 1-in-10 year weather.

[9] The load impact model based on the ex post analysis covers only a four hour event window, as all events lasted four hours. In producing ex ante estimates for a five hour event window, FSC used the coefficients from the four-hour event model in computing estimates for ex ante event hours 1, 2, 4 and 5. The load impact for hour 3 is based on the average coefficients from hours 2 and 3 from the ex post model.

Table 4-4
Summer Saver Enrollment Projections
(Air Conditioning tons)

Date	All Customers	Residential Customers			Commercial Customers		
		All	50% Cycling	100% Cycling	All	30% Cycling	50% Cycling
Feb., 2010	144,290	96,899	48,531	48,368	47,391	18,426	28,965
Jan., 2011	157,880	107,067	49,435	57,633	50,813	19,522	31,291
Jan., 2012	169,072	115,441	50,179	65,262	53,631	20,424	33,207

Tables 4-5 through 4-7 below contain estimates of ex ante load impacts for the typical event day and each monthly system peak day under 1-in-2 and 1-in-10 year weather conditions for residential participants, commercial participants and the program as a whole, respectively. These are based on projected enrollment in the steady state year, 2012. For a typical event day and 1-in-2 year weather conditions, aggregate impacts equal 22.8 MW. The estimate for a typical event day under 1-in-10 year conditions is 19% higher. On the highest peak day for 1-in-2 year weather conditions, the load reduction is estimated to equal 28.8 MW. With the more extreme 1-in-10 year conditions, the estimated impact is 31.9 MW.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather, the very low temperature in June, reflecting the well known "June Gloom" typically experienced in San Diego, results in very small average and aggregate load impact estimates. The June value is more than 80% lower than the September estimate, which is the highest of any month. Based on 1-in-10 year weather conditions, the June estimate is more than five times higher than the 1-in-2 year estimate. Indeed, the June value based on 1-in-10 year weather is 90% of the highest monthly estimate based on 1-in-2 year weather. The weather conditions on the monthly system peak day in May produce the lowest value based on 1-in-10 year weather, followed by October. The highest load impacts are in September in the 1-in-10 weather year, with the system peak estimate equaling 23.6 MW.

Table 4-5
Average and Aggregate Load Reductions by Day Type and Weather Year
All Residential Summer Saver Participants
Forecast Year 2012

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Temperature (°F)
1-in-2	Typical Event Day	0.52	0.15	17.0	84.0
	May Monthly Peak	0.39	0.11	12.9	82.5
	June Monthly Peak	0.11	0.03	3.6	77.4
	July Monthly Peak	0.46	0.13	15.2	82.1
	August Monthly Peak	0.53	0.15	17.5	83.9
	September Monthly Peak	0.64	0.18	21.1	87.7
	October Monthly Peak	0.51	0.15	16.9	86.8
1-in-10	Typical Event Day	0.61	0.17	20.1	86.5
	May Monthly Peak	0.43	0.12	14.0	86.3
	June Monthly Peak	0.58	0.17	19.1	87.4
	July Monthly Peak	0.59	0.17	19.5	86.8
	August Monthly Peak	0.65	0.19	21.4	86.5
	September Monthly Peak	0.72	0.20	23.6	88.7
	October Monthly Peak	0.55	0.16	18.0	87.8

Table 4-6
Average and Aggregate Load Reductions by Day Type and Weather Year
All Commercial Summer Saver Participants-Forecast Year 2012

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Temperature (°F)
1-in-2	Typical Event Day	0.46	0.11	5.7	82.1
	May Monthly Peak	0.35	0.08	4.3	80.4
	June Monthly Peak	0.16	0.04	1.9	75.8
	July Monthly Peak	0.43	0.10	5.3	80.8
	August Monthly Peak	0.47	0.11	5.8	82.1
	September Monthly Peak	0.57	0.13	7.1	86.0
	October Monthly Peak	0.43	0.10	5.3	83.9
1-in-10	Typical Event Day	0.58	0.13	7.2	84.9
	May Monthly Peak	0.42	0.10	5.2	84.7
	June Monthly Peak	0.52	0.12	6.5	84.7
	July Monthly Peak	0.52	0.12	6.4	84.5
	August Monthly Peak	0.60	0.14	7.4	84.5
	September Monthly Peak	0.67	0.15	8.3	87.2
	October Monthly Peak	0.49	0.11	6.1	86.4

Table 4-7
Average and Aggregate Load Reductions by Day Type and Weather Year
All Summer Saver Participants –Forecast Year 2012

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Temperature (°F)
1-in-2	Typical Event Day	0.50	0.13	22.8	83.4
	May Monthly Peak	0.38	0.10	17.3	81.9
	June Monthly Peak	0.13	0.03	5.6	76.9
	July Monthly Peak	0.45	0.12	20.4	81.7
	August Monthly Peak	0.51	0.14	23.3	83.3
	September Monthly Peak	0.62	0.17	28.2	87.2
	October Monthly Peak	0.49	0.13	22.2	85.9
1-in-10	Typical Event Day	0.60	0.16	27.2	86.0
	May Monthly Peak	0.42	0.11	19.2	85.8
	June Monthly Peak	0.56	0.15	25.6	86.6
	July Monthly Peak	0.57	0.15	25.9	86.0
	August Monthly Peak	0.63	0.17	28.8	85.9
	September Monthly Peak	0.70	0.19	31.9	88.2
	October Monthly Peak	0.53	0.14	24.1	87.4

4.5 Recommendations for Changes

SDG&E should examine the relative incentives paid for two cycling options that residential customers can select. There is a clear selection bias that occurs in that customers with higher loads are more likely to select the 50% cycling option, which in part explains the rather modest differential (about 30%) in the average load impacts between customers who select the 100% option compared with those on the 50% cycling option. This is significantly less than the payment differential for customers on those options. A reduction in the incentives paid to the 100% cycling group combined with an increase in the incentives paid to the 50% cycling group could increase program enrollment while reducing costs and increasing cost-effectiveness. The lower incentive for the 100% cycling group might risk losing some participants, but the higher payment to the 50% cycling group would likely more than make up for this loss and could reduce program costs while possible increasing aggregate load impacts.

SDG&E should also consider calculating the correlation between monthly electricity use and cooling degree hours for each customer in the service territory and using this variable as a means of targeting high value customers for future recruitment. This variable is a strong driver of load impacts and can be used to identify and recruit customers who will increase the average load reduction among program participants.

5 Summary of SDG&E's BIP Report

5.1 Program Description

BIP is a tariff based, emergency-triggered demand response program that the California Independent System Operator (CAISO) can dispatch when a stage1 alert is forecasted, and the utilities can dispatch for local emergencies. Customers enrolled in BIP receive incentive payments in exchange for committing to reduce their electrical usage to a contractually-established level referred to as the Firm Service Level (FSL). Participants who fail to reduce their load to their FSL are subject to a financial penalty assessed on a kW per hour basis. BIP option A (BIP-A) requires load reduction response in 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. BIP option B

(BIP) requires load reduction response in 3 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. BIP events may be called any day of the year. Enrollment in BIP-A in January 2010 was 18 customers and enrollment or BIP-B equaled 1 customer.

5.2 BIP ex-ante forecast

For ex ante analysis, the estimated load reduction for BIP is a function of: the forecasted load in the absence of a DR event (i.e. the reference load), the participant's FSL, and estimates of over or under performance. The reference load is estimated using a regression model discussed below. The regression models used to predict reference loads were developed with the primary goal of accurately predicting the average customer load given time-of-day, day-of-week, month, and temperature. Given that all BIP customers are on TOU rates, rate period variables were also included in the model specification. Dynamic lags – using load in prior periods to predict load at time *t* – were included in the ex post analysis for 24 hours prior and two weeks prior. These lags were not used in the ex ante analysis methodology presented in this section because the actual load 24 hours to two weeks prior is unknown when forecasting load many years forward. The estimated models were based on hourly load data for each customer from 2007 to 2009. For SDG&E, the ex ante load impact was determined simply by decreasing usage from the reference load to the FSL when the event begins, and then increasing it back up to the reference load in the hour after the event.

The dependent variable in the ex ante 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. Mathematically, the regression model can be expressed as:

$$
\begin{aligned}
kW_t = {} & A + B \times SummerOn_t + C \times SummerMid_t + D \times SummerOff_t + E \times WinterMid_t \\
& + \sum_{i=1}^{24}\sum_{j=1}^{5} F_{ij} \times Hour_i \times DayType_j + \sum_{i=1}^{24}\sum_{j=1}^{12} G_{ij} \times Hour_i \times Month_j \\
& + \sum_{i=1}^{24}\sum_{j=2008}^{2009} H_{ij} \times Hour_i \times Year_j + \sum_{i=1}^{24} I_{ij} \times Hour_i \times CDD_t \\
& + \sum_{i=1}^{24} J_{ij} \times Hour_i \times CDDsqr_t + \sum_{i=1}^{24} K_{ij} \times Hour_i \times HDD_t \\
& + \sum_{i=1}^{24} L_{ij} \times Hour_i \times HDDsqr_t + \sum_{i=1}^{24}\sum_{j=1}^{3} M_{ij} \times Hour_i \times Eventday_j + e_t
\end{aligned}
$$

In this equation,

kW_t represents the hourly BIP customer load at time t;

A is the estimated constant term;

B through M_{ij} are the estimated parameters;

$SummerOn_t$, $SummerMid_t$, $SummerOff_t$ and $WinterMid_t$ are binary variables that indicate which TOU rate block is in effect for each hour;

$Hour_i$ is a 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;

$DayType_j$ is a series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday);

$Month_j$ is a series of binary variables for each month;

$Year_j$ is a series of binary variables for each year (2007-2009);

CDD_t is the number of cooling degree days (base 65) in interval t;

$CDDsqr_t$ is the number of cooling degree days squared;

HDD_t is the number of heating degree days (base 65) in interval t;

$HDDsqr_t$ is the number of heating degree days squared;

$Eventday_j$ is a binary variable representing each event day,[10] and;

e_t is the error term.

[10] SCE had three events during the time period included in the estimation, whereas PG&E and SDG&E had two events.

In decision D.09-08-027 the utilities were directed not to market the BIP program until a final decision on the phase 3 of rulemaking R-07-01-041 was issued. The final decision on phase 3 of the rulemaking has not been issued so no growth in the number of customers was assumed for the BIP program.

6 Summary of SDG&E's CPP-E report

6.1 Program Description

The Critical Peak Pricing-Emergency (CPP-E) schedule is an optional commodity tariff that offers customers the opportunity to respond to local Utility emergency situations and to manage their electric costs by either reducing load during high cost pricing periods or shifting load from high cost pricing periods to lower cost pricing periods. This schedule is available to non-residential customers served under a time of use (TOU) rate schedule with an annual maximum demand of 20 kilowatts (kW) or greater currently receiving bundled utility service who have an Interval Data Recorder (IDR) meter installed with related telecommunications capability, compatible with the Utility's meter reading and telecommunication system. Participating customers are called upon with very short advance notice (30 minutes) on a day-of basis. CPP-E is designed for customers who have the ability to modify their business operations and reduce load with extremely short notice. CPP-E events are activated during a system reliability emergency as determined by SDG&E which may include but is not limited to a CAISO stage 1 or stage 2 alert, or when local grid operators determine that firm load reliability is threatened. CPP provides for a maximum of 80 event hours per year with events limited to no more than 6 hours per day, 4 days per week and 40 hours per month. Events may be called on any day of the year at any hour of the day. No events were called in 2009.

6.2 CPP-E Ex-Ante Summary

The ex-ante CPP-E forecast is based on the 3 events that took place in 2007. The average MW achieved over all three events was 2.3 MW. The load reduction for the 1st event was 2.3 MW, the load reduction for the second event was 2.8 MW and for the third event was 2.2 MW. Temperature was insignificant in the 2007 regression estimates so the ex-ante results do not change with temperature and therefore are constant over the monthly peak days and the 1 in 2 and 1 in 10 weather years. The forecast assumes that there is no growth in the number of customers on the rate since there has been no growth in customers on the rate since 2007, and there are no plans to increases the number of customers on the rate.

7 Summary of SDG&E's AMP Report

7.1 Program Description

The SDG&E AMP program is scheduled to begin in 2010 and includes 1 aggregator contract. Events for this contract are triggered day-of with a 30 minute notification window. Event may be called between May and October each year, between 12pm-6pm and the maximum event length is 5 hours. Events may also be called outside of the months, and the aggregator will receive an energy payment, but the aggregator will not be subject to a capacity penalty. The contract calls for the aggregator to have 25 MW by May of 2010, 35 MW by May of 2011 and 40 MW by May of 2012.

7.2 AMP Ex-Ante Summary

Reference loads and per-customer load impacts are based on the historical load data and estimated ex-post load impacts for the customer accounts enrolled in CBP DO by the aggregator enrolled in AMP. Since CBP customer were used, the regression model and ex-ante methodology are the same as the methodology presented in the CBP section of this report. The enrollment forecast was based partially on the growth rate of the CBP program in 2007 and 2008 and partially on the contract amount. The contract calls for 25 MW by May of 2010. Even with the customers the aggregator already has in CBP this requires growth faster than the 8 MW of growth achieved by the CBP program in 2007 and 2008.Therefore the enrollment forecast of the number of customers assumes that the aggregator is one year behind in meeting their contract amounts. The forecast predicts that the aggregator will meet their 2010 goal in 2011, their 2011 contract amount in 2012 and so on.

8 Summary of the Peak Time Rebate Report

8.1 Program Description

The peak time rebate program is scheduled to begin in May of 2011. All residential customers will be automatically enrolled in this program. Events last from 11am-6pm and can be triggered either day-ahead or day-of. PTR events may be called on any day of the year and there is no limit on the number of events. Customers enrolled on PTR will receive a bill credit of $0.75 per kw if there usage on event days is lower than their customer reference level. PTR customers with enabling technology receive a higher bill credit of $1.25 per kw.

8.2 PTR Ex-Ante Forecast

There are five major assumptions required to compute the expected PTR load reduction from residential customers. 1) The meter deployment rate, 2) the rebate price, 3) the participation rates, 4) the average load, and 5) the elasticities which determine the percent impact per customer when combined with the prices. The rebate price is $0.75 as adopted in SDG&E's GRC phase II decision. The participation rate used is 50% which is consistent with the AMI decision D-07-04-043. The average load is based on SDG&E's load research and daily load profile data. Load data from 2005 is used for the 1 in 2 year estimates and data from 2007 is used for the 1 in 10 year estimates. The meter deployment assumptions and elasticities are discussed in more detail below.

The meter deployment plan for the smart meter deployment began in 2009 and as of March 29th 2010 391,126 electric meters have been installed. Customers will become eligible for PTR once they have had a smart meter in place for three months and it has been tested and validated. As of May 2011 99% of residential customers are forecasted to have a smart meter installed.

For the residential sector analysis, impact estimates are based on price elasticities derived from the Statewide Pricing Pilot (SPP), tailored to reflect the weather conditions and Central Air Conditioning (CAC) saturations of SDG&E's customers. Equation (3) in Section 3.1 of the SPP Final Report (March 16, 2005), shown below for convenience, was estimated from data on SPP customers in the CPP-F treatment and control cells.

$$\ln\left(\frac{Q_p}{Q_{op}}\right)=\alpha+\sum_{i=1}^{N}\theta_i D_i+\sigma\ln\left(\frac{P_p}{P_{op}}\right)+\delta(CDH_p-CDH_{op})+\lambda(CDH_p-CDH_{op})\ln\left(\frac{P_p}{P_{op}}\right)$$
$$+\phi(CAC)\ln\left(\frac{P_p}{P_{op}}\right)+\varepsilon$$

Where

Q_p = average daily energy use per hour in the peak period

Q_{op} = average daily energy use per hour in the off-peak period

σ = the elasticity of substitution between peak and off-peak energy use

P_p = average price during the peak pricing period

P_{op} = average price during the off-peak pricing period

δ = measure of weather sensitivity

λ = the change in elasticity of substitution due to weather sensitivity

CDH_p = average cooling degree hours per hour (base 72 degrees) during the peak pricing period

CDH_{op} = average cooling degree hours per hour (base 72 degrees) during the off-peak pricing period

ϕ = the change in elasticity of substitution due to the presence of central air conditioning

CAC = 1 if a household owns a central air conditioner, 0 otherwise

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are a total of N customers.

θ_i = fixed effect for customer

ε = regression error term.

The composite elasticity of substitution (ES) in this model is a function of three terms, as shown below:

$$\text{ES}=\sigma+\lambda(CDH_p-CDH_{op})+\phi(CAC) \qquad (2)$$

The estimated values for σ, λ and ϕ are, respectively, -0.03073, -0.00187 and -0.09107. The elasticities for the base case residential analysis were derived by multiplying the coefficients in equation 2 by the CAC saturations for each of SDG&E's two climate zones and by the values for the weather term for each zone and day type. The saturation of central air conditioning for residential customers in SDG&E's service territory is 49 percent in the Inland climate zone and 26 percent in the Coastal climate zone.

The daily elasticities reported in the table are derived in a similar manner (i.e., by substituting the relevant weather and CAC saturation data into the daily model estimated from the SPP data). The model is similar to the one shown above except that the dependent variable is daily electricity use rather than the ratio of daily use in each period, and the price term is average daily price. Equations 3 and 4 represent the daily demand model and the effective daily price elasticity of daily energy use.

$$\ln(Q_D)=\alpha+\sum_{i=1}^{N}\theta_i D_i+\eta\ln(P_D)+\rho(CDH_D)+\chi(CDH_D)\ln(P_D)$$
$$+\xi(CAC)\ln(P_D)+\varepsilon \qquad (3)$$

Where

Q_D = average daily energy use per hour

η = the daily price elasticity

P_D = average daily price

ρ = measure of weather sensitivity

χ = the change in daily price elasticity due to weather sensitivity

CDH_D = average daily cooling degree hours per hour (base 72 degrees)

ξ = the change in daily price elasticity due to the presence of central air conditioning

CAC = 1 if a household owns a central air conditioner, 0 otherwise

θ_i = fixed effect for customer i

D_i = a binary variable equal to 1 for the i^{th} customer, 0 otherwise, where there are

a total of N customers.

ε = regression error term.

The composite daily price elasticity of substitution in this model is a function of three terms, as shown below:

$$\text{Daily}=\eta+\chi(CDH_D)+\xi(CAC) \qquad (4)$$

The values for η, χ and ξ, respectively, are -0.03966, 0.00121 and -0.01573.

.

The SPP demand models forecast the change in on-peak and off-peak consumption on event days. The load impact protocols require that results be reported by hour. First, the original SPP models were used to forecast the total load drop during the peak period and then the results per hour were created using the results of an hourly analysis performed by CRA of residential customers on Track A of the SPP.

9 Portfolio Analysis

Customers can participate in both the CPP-D rate and BIP, the CPP-D rate and CBP DO, and in CPP-D and the AMP contract. Since CPP-D was classified as an energy program in D.09-08-027 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 AMP, BIP or CBP DO along with CPP-D had to be subtracted from the CPP-D enrollment forecast. Since all BIP customers are bundled customers and no growth was predicted for the program the existing BIP customers also enrolled on CPP-D were subtracted from the CPP-D enrollment forecast. Both the CBP and AMP programs allow direct access customers to enroll in the programs the percentage of bundled customers enrolled on each program needed to be estimated. In 2009 58% of customers on CBP DO were bundled and 75% of the CBP DO customers enrolled with the aggregator moving to the AMP program were bundled. Once the number of bundled customers is determined the next step is to determine what the percentage of the bundled customers enrolled on AMP or CBP DO are also enrolled on CPP-D. This was estimated using the CPP-D opt out percentages. Combining the bundled percentages with the CPP-D opt-out percentage provided a forecast of the number of customers on both CPP-D and CBP-DO or AMP. These customers were subtracted from the CPP-D enrollment forecast. One other area needed adjustment for the portfolio analysis. In 2009 there were CBP DO and CPP-D events called on the same day. This could cause the CPP-D impact per customer to be overestimated if CBP DO Impact are higher than CPP-D impacts. To counteract this issue the portfolio CPP-D forecast uses impact per customers based on only the non-CBP DO CPP-D customers.

There are two other areas of multiple program participation that were considered but not included in the final analysis. In 2013 dual participation may occur between CPP-D and summer saver. However, most of the summer saver impact is incremental because it comes form an enabling technology, the majority of Summer Saver commercial customers are less than 20 kW and therefore not eligible for the CPP-D rate, on top of that some medium commercial customer will opt –out of the CPP-D rate. Once all these factors are combined the forecasted overlap between the two programs is less than 1 MW and therefore was not included in the final analysis. Similarly customers may participation in both PTR and Summer Saver; however the PTR forecast assumes no enabling technology so the summer saver results are incremental to any load reduction that will be achieved by the PTR program.