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2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRate™—Peak Day Pricing and TOU Tariffs and SmartAC Program

Volume 2: Ex Ante Load Impacts

Final Report

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TABLE OF CONTENTS

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1. EXECUTIVE SUMMARY

This report is the second of two volumes that document the load impact analysis, methodology, and results for the following Pacific Gas and Electric Company (PG&E) demand response tariffs and programs:

- Residential SmartRate™,[1] in both its current form as well as in a revised structure, referred to here as Peak Day Pricing (PDP), that will replace SmartRate starting in 2011;
- Residential time-of-use (TOU) tariffs E6 and E7;
- The SmartAC™ program for residential and non-residential customers.

This volume documents the ex ante analysis and results for the above programs and tariffs for 2010 through 2020. Ex post impacts for 2009 are presented in Volume 1.

1.1. RESIDENTIAL SMART RATE AND PEAK DAY PRICING LOAD IMPACT SUMMARY

In May, 2008, PG&E began offering a critical peak pricing tariff known as SmartRate to residential and small commercial customers in the Bakersfield and greater Kern County area. Starting in May 2009, enrollment expanded both in terms of the number of customers and the geographic regions covered as SmartMeter™ deployment progressed. At the beginning of the 2009 program season, roughly 8,500 residential customers were enrolled in the program and by the end of September 2009, more than 22,000 customers were enrolled. At the time this report was written, active enrollment equaled approximately 25,500 customers.

PG&E will continue to market SmartRate to residential customers through the first half of 2010, targeting high-use, high-response customers. Based on the February 25, 2010 decision on PG&E's Peak Day Pricing filing,[2] SmartRate will no longer be available starting in 2011. The ex ante enrollment forecasts underlying the load impact estimates presented here are based on the key elements contained in that decision, which include:

- The current SmartRate option available to residential customers will remain in effect until February 2011, at which time SmartRate customers will be moved to the new residential PDP rate unless the customer opts out to a non-time differentiated residential tiered rate.
- There will be between 9 and 15 PDP event days per calendar year.
- All customers that are defaulted to, or choose, PDP rate will be afforded bill protection for the first year, unless they choose to wave such protection.

[1] Any use of the term SmartMeter, SmartRate or SmartAC in this document is intended to refer to the trademarked term, whether or not TM is included. SmartMeter™ is a trademark of SmartSynch, Inc. and is used by permission.
[2] CPUC Decision 10-02-032. Decision on Peak Day Pricing for Pacific Gas and Electric Company. February 25, 2010 (Issued 3/2/10). A 09-02-022.

- All Customers subject to PDP will have a hedging option to reduce bill volatility. For residential customers, this decision will give each customer the option of facing PDP prices on every PDP event day, or on alternating event days.

The PDP tariff option approved by the CPUC is an overlay on tariff E1, and has a relatively high peak period price on PDP days and a very small price differential between peak and off-peak prices on other weekdays. Although it has time-varying pricing on all weekdays, because of the very modest price differential on non-PDP days, the effective price signals associated with PDP are quite similar to SmartRate, which did not have time-varying pricing on days other than event days.

The ex ante load impacts presented here are based on an enrollment strategy that assumes PG&E will identify and rank high performer, high likelihood customers and market to these high value customers in descending order over the forecast horizon. Figure 1-1 summarizes the process used to identify the highest value customers.

A model quantifying the extent to which customer characteristics, weather, central AC penetration, notifications, and various other factors affect price responsiveness was developed based on SmartRate impact analysis and applied to the entire PG&E residential population. It was combined with individual customer estimates of the likelihood of enrollment under the most effective marketing approach based on extensive analysis of actual customer choice data as a function of promotional strategies and customer characteristics. The information on high price responsiveness and high enrollment likelihood was used to produce a customer level value ranking to better optimize targeting. PG&E has not yet developed marketing plans for PDP starting in 2011. The targeting strategy underlying the enrollment forecasts presented here is conceptually consistent with PG&E's 2010 SmartRate marketing plan, although the specific models and tactics underlying the forecasts presented here and those currently being used by PG&E differ.

Figure 1-1
Overview of SmartRate/PDP Enrollment Forecast Process

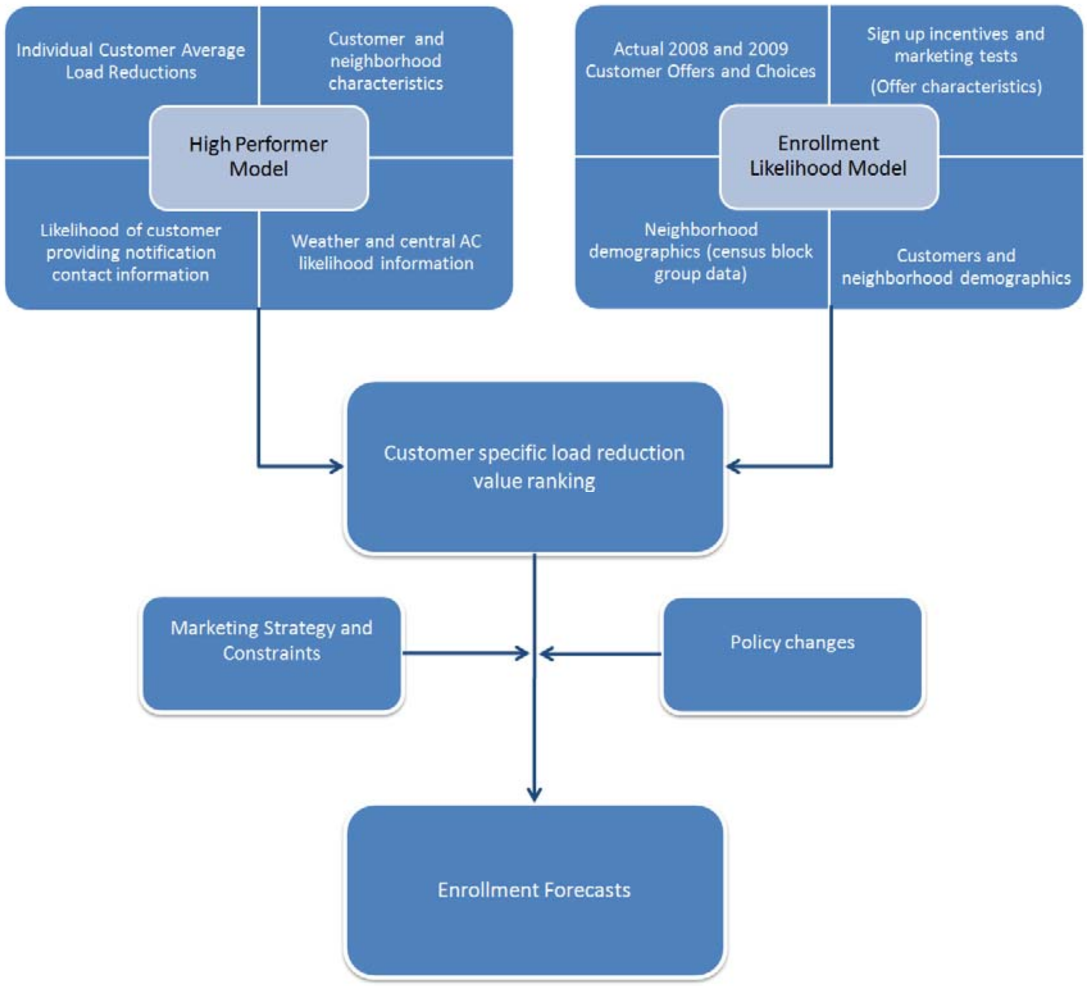

Table 1-1 summarizes the projected program load reduction capabilities for SmartRate/PDP for each forecast year under 1-in-2 and 1-in-10 year weather conditions. The table shows the average load reduction across the five hour event period for a typical event day. The table contains a significant amount of information that underlies the aggregate load impacts presented in the sixth column, which grow from roughly 43 MW in 2010 under 1-in-2 year weather conditions to more than 121 MW by 2020. Based on 1-in-10 year weather conditions, the aggregate impacts grow from approximately 53 MW in 2010 to almost 147 MW in 2020.

Underlying both sets of estimates are the enrollment projections that show program participation growing from roughly 82,000 customers in 2010 to almost 300,000 customers in 2020. Importantly, the annual estimates reflect a drop in enrollment in 2012, following the end of the one year bill protection period for SmartRate enrollees who are defaulted onto PDP in early 2010. Enrollment is estimated to fall from 122,721 in 2011 to 86,795 in 2012, and then to more than triple by 2020. This drop in enrollment reflects a fundamental difference in the revenue neutrality of the SmartRate and PDP tariffs. SmartRate was not designed to be revenue neutral for the average PG&E customer. Rather, SmartRate was designed to be revenue neutral for the average customer in hot climate zones R and S as the objective was to attract customers with large loads that could provide large load reductions. PDP, on the other hand, was designed to be revenue neutral for the average customer across the entire PG&E service territory. As such, the high use customers that will be defaulted onto PDP at the beginning of 2011 as directed by the CPUC (many of whom reside in zones R and S) will be more likely to leave at the end of the bill protection period than will an average PG&E customer.

Aggregate load impact estimates follow a similar pattern to that of the enrollment forecasts, dropping from 67 MW in 2011 to 52 MW in 2012, and then growing by more than a factor of 2 by 2020. The difference in the growth rates for enrollment and load reduction reflects the marketing strategy outlined above, in which high load impact, high enrollment potential customers are recruited in the early years while lower impact customers are enrolled in the later years. This strategy is reflected in the fall in the percent load reduction across years shown in the seventh column in the table and in the drop in the saturation of central air conditioning underlying the load impacts shown in the last column in the table.

Table 1-1
Aggregate Ex-Ante Load Impacts for SmartRate/PDP by Year
(Hourly Average Reduction in MW Over the Five Hour Peak Period from 2 to 7 pm)

System Conditions	Year	# of Accounts	Avg. Reference Load (MW 2-7 pm)	Average Estimated Load with DR (MW 2-7 pm)	Load Impact (MW 2-7 pm)	% Load Reduction (2-7 pm)	Avg. Temp. (F)	Central AC (%)
1-in-2 Typical Event Day	2010	81,784	154.7	111.4	43.3	28.0%	95.4	49.8
	2011	122,721	219.0	152.2	66.9	30.5%	96.3	55.8
	2012	86,795	168.4	116.8	51.6	30.6%	97.1	60.4
	2013	142,404	267.8	186.5	81.3	30.4%	96.8	59.7
	2014	169,604	303.7	215.0	88.7	29.2%	96.3	57.5
	2015	193,572	333.4	239.1	94.3	28.3%	95.9	55.7
	2016	219,111	364.1	263.3	100.8	27.7%	95.6	54.0
	2017	241,909	390.7	284.3	106.4	27.2%	95.3	52.7
	2018	261,974	413.5	302.3	111.1	26.9%	95.1	51.6
	2019	280,801	436.0	320.1	116.0	26.6%	95.0	50.8
	2020	299,238	459.9	338.6	121.4	26.4%	94.9	50.3
1-in-10 Typical Event Day	2010	81,784	185.6	133.1	52.5	28.3%	98.5	49.8
	2011	122,721	264.3	183.1	81.3	30.7%	99.3	55.8
	2012	86,795	203.2	140.7	62.6	30.8%	100.2	60.4
	2013	142,404	323.5	224.7	98.7	30.5%	99.9	59.7
	2014	169,604	366.4	258.7	107.7	29.4%	99.4	57.5
	2015	193,572	401.6	287.3	114.3	28.5%	99.1	55.7
	2016	219,111	438.1	316.1	122.0	27.9%	98.8	54.0
	2017	241,909	469.7	341.0	128.7	27.4%	98.6	52.7
	2018	261,974	496.8	362.4	134.4	27.1%	98.4	51.6
	2019	280,801	523.5	383.4	140.2	26.8%	98.3	50.8
	2020	299,238	551.9	405.3	146.6	26.6%	98.2	50.3

Table 1-2 shows the average peak load reduction for PDP for each event hour based on estimated enrollment in 2020. As seen, aggregate load impacts in the summer months typically peak between 4 and 5 pm, although in June, the peak hour is from 5 to 6 pm. The maximum peak hour load reduction based on 1-in-2 year weather conditions is 153.2 MW in the hour from 4 to 5 pm in July. The maximum based on 1-in-10 year weather conditions occurs during the same hour and month, where the load reduction equals 168.5 MW, or roughly 10% more than under normal year weather conditions.

Table 1-2
SmartRate/PDP Aggregate Impacts (MW) by Hour and Month Based on Enrollment in 2020 (Monthly System Peak Day)

System Conditions	Year	Accounts	Avg. Reference Load	Average Estimated Load with DR	Load Impact	% Load Reduction	Avg. Weighted Temperature
			(MW 12-6 pm)	(MW 12-6 pm)	(MW 12-6 pm)	(12-6 pm)	(F)
1-in-2 Annual Peak	2010	66,823	180.5	135.7	44.8	24.8%	92.4
	2011	64,558	174.4	131.1	43.2	24.8%	92.4
	2012	62,369	168.5	126.7	41.8	24.8%	92.4
	2013	60,255	162.8	122.4	40.4	24.8%	92.4
	2014	58,212	157.2	118.2	39.0	24.8%	92.4
	2015	56,239	151.9	114.2	37.7	24.8%	92.4
	2016	54,332	146.8	110.4	36.4	24.8%	92.4
	2017	52,490	141.8	106.6	35.2	24.8%	92.4
	2018	50,711	137.0	103.0	34.0	24.8%	92.4
	2019	48,992	132.3	99.5	32.8	24.8%	92.4
	2020	47,331	127.8	96.1	31.7	24.8%	92.4
1-in-10 Annual Peak	2010	66,823	187.5	140.4	47.1	25.1%	93.3
	2011	64,558	181.1	135.6	45.5	25.1%	93.3
	2012	62,369	175.0	131.0	43.9	25.1%	93.3
	2013	60,255	169.0	126.6	42.5	25.1%	93.3
	2014	58,212	163.3	122.3	41.0	25.1%	93.3
	2015	56,239	157.8	118.1	39.6	25.1%	93.3
	2016	54,332	152.4	114.1	38.3	25.1%	93.3
	2017	52,490	147.2	110.3	37.0	25.1%	93.3
	2018	50,711	142.3	106.5	35.7	25.1%	93.3
	2019	48,992	137.4	102.9	34.5	25.1%	93.3
	2020	47,331	132.8	99.4	33.4	25.1%	93.3

1.2. RESIDENTIAL TOU TARIFF LOAD IMPACT SUMMARY

PG&E has had a traditional TOU tariff in place for many years. The E7 tariff is a two-period, five-tier tariff. The peak period for the E7 tariff is from noon to 6 pm on weekdays, with off-peak prices in effect at all other times. The peak period is the same the entire year. The E7 rate has been closed to new customers since 2007. It was replaced by the E6 tariff, which is a three-period, five-tier TOU rate. With the E6 tariff, the peak period is from 1 pm to 7 pm in the summer months. The partial peak period in the summer is from 10 am to 1 pm and 7 pm to 9 pm, Monday through Friday and from 5 pm to 8 pm on Saturdays and Sundays. In the winter, peak period prices do not apply, and partial peak prices occur from 5 pm to 8 pm on weekdays only.

A substantial number of E6 and E7 customers are net metered. Net metered customers typically have very different load patterns compared with standard metered customers, as they very often have solar power or some other form of distributed generation. Approximately 16% of E7 customers and 81% of E6 customers are net metered. The load impact estimates presented here exclude net metered customers, as the data used in the analysis only apply to standard metered customers.

As discussed above, TOU rate E7 is closed to future enrollment. In addition, PG&E has no plans to actively market TOU rate E6, focusing instead on the higher impact SmartRate and PDP tariffs. As such, cumulative enrollment estimates for these tariffs in each year are simply based on what enrollment was in the prior year minus attrition. The annual attrition rate of 3.39% was derived by a review of attrition rates for customers on the tariff in 2008 and 2009.

Table 1-3 summarizes the projected load reduction on the annual system peak day for each year for the combined E6 and E7 standard metered customer group under 1-in-2 and 1-in-10 year weather conditions. Based on 1-in-2 year weather conditions, aggregate average peak period load reductions equal 44.8 MW for the roughly 67,000 customers enrolled in 2010 and fall to 31.7 MW by 2020, as enrollment drops to approximately 47,000 customers. The percent load drop does not vary from year to year because the customer mix is not changing, although attrition leads to lower aggregate impacts in later years.

Table 1-3
Aggregate Ex-Ante Load Impacts for Residential TOU Tariffs by Year
(Average Peak Period Reduction on Annual System Peak Day)

System Conditions	Year	Accounts	Avg. Reference Load	Average Estimated Load with DR	Load Impact	% Load Reduction	Avg. Weighted Temperature
			MW (12-6 pm)	MW (12-6 pm)	MW (12-6 pm)	(12-6 pm)	(F)
1-in-2 Annual Peak	2010	66,823	180.5	135.7	44.8	24.8	92.4
	2011	64,558	174.4	131.1	43.2	24.8	92.4
	2012	62,369	168.5	126.7	41.8	24.8	92.4
	2013	60,255	162.8	122.4	40.4	24.8	92.4
	2014	58,212	157.2	118.2	39.0	24.8	92.4
	2015	56,239	151.9	114.2	37.7	24.8	92.4
	2016	54,332	146.8	110.4	36.4	24.8	92.4
	2017	52,490	141.8	106.6	35.2	24.8	92.4
	2018	50,711	137.0	103.0	34.0	24.8	92.4
	2019	48,992	132.3	99.5	32.8	24.8	92.4
	2020	47,331	127.8	96.1	31.7	24.8	92.4
1-in-10 Annual Peak	2010	66,823	187.5	140.4	47.1	25.1	93.3
	2011	64,558	181.1	135.6	45.5	25.1	93.3
	2012	62,369	175.0	131.0	43.9	25.1	93.3
	2013	60,255	169.0	126.6	42.5	25.1	93.3
	2014	58,212	163.3	122.3	41.0	25.1	93.3
	2015	56,239	157.8	118.1	39.6	25.1	93.3
	2016	54,332	152.4	114.1	38.3	25.1	93.3
	2017	52,490	147.2	110.3	37.0	25.1	93.3
	2018	50,711	142.3	106.5	35.7	25.1	93.3
	2019	48,992	137.4	102.9	34.5	25.1	93.3
	2020	47,331	132.8	99.4	33.4	25.1	93.3

1.3. RESIDENTIAL SMARTAC LOAD IMPACT SUMMARY

PG&E's SmartAC™ program involves the installation of programmable communicating thermostats (PCTs) and/or direct load control switches (switches) in households and small/medium businesses with central air conditioning. The control devices allow air conditioning equipment to be cycled or thermostats to be adjusted[3] when an event is triggered, thereby reducing energy demand associated with air conditioning load. SmartAC events can only be called under emergency or in anticipation of emergency conditions between May 1st and October 31st and for an event period of six hours or less for no more than 100 hours per season.

PG&E began marketing the SmartAC program in early 2007. Most marketing has been done using direct mail. To date, most residential participants were paid a one-time fee of $25 to allow installation of one or more devices at their premise. In August 2009, PG&E submitted a request to the CPUC to modify the goals and budgets for SmartAC.[4] In this filing, PG&E proposed a target of 206,000 SmartAC residential customers by year-end 2011, providing a peak load impact of 209 MW.

The enrollment estimates used in this report are the same as those that underlie the load impact estimates contained in PG&E's August 2009 filing. These estimates are based on a significant shift in marketing methods and strategies from what was used in the past, as delineated in both the 2009 update filing and the SmartAC 2009 Annual Report.[5] While FSC developed a model of SmartAC enrollment as a function of promotional features and customer characteristics based on 2009 direct mail marketing and enrollment data, the model was not used because it could not capture the impact of some of the new promotional methods and direction that PG&E will use to market SmartAC in 2010 and 2011, including PG&E's new psychometric targeting, the SmartAC Affiliate Program, the Refer-a-Friend Program and others. As of January, 2010, SmartAC had 124,000 residential customers. This is an increase of 16,000 over June 2009. As indicated above, enrollment is expected to increase to 206,000 customers by the end of 2011.

It should also be noted that the enrollment projections presented here ignore the potentially very significant effect that a Peak Time Rebate program could have on SmartAC enrollment. PG&E filed testimony in the PTR proceeding on February 26th.[6] In this filing, PG&E proposed a two-tiered PTR program, in which customers who are also enrolled in SmartAC and agree to have their air conditioners cycled on PTR days would be paid a higher incentive than customers who do not agree to have their air conditioner controlled. If this program is approved, it could significantly increase enrollment in SmartAC. The CPUC is expected to rule on this application sometime in late 2010. The impact of PTR on SmartAC enrollment will be factored into future impact evaluations. Because of the uncertainty around these regulatory decisions, for this report, we have held SmartAC enrollment constant at 206,000 residential customers from 2012 to 2020.

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[3] Air conditioner cycling can be done with either load control devices or thermostats, while thermostats can also be used to reduce air conditioning use by adjusting temperature settings.
[4] A.09-08-018, *Application of Pacific Gas and Electric Company (U 39 E) for Approval of 2010-2011 SmartACTM Program and Budget ;Pacific Gas and Electric Company Prepared Testimony.*
[5] *Annual Report on Pacific Gas and Electric Company's 2009 SmartAC™ Program*. December 31, 2009.
[6] A.10-02-028 2010 Rate Design Window, Peak Time Rebate for Approval of funding request for years 2010-2013.

Table 1-4 shows the program-specific aggregate load impacts for the SmartAC program for each monthly system peak day and typical event day based on each weather year and all forecast years in which enrollment changes. The program specific impacts on a typical event day grow by roughly 40% between 2010 and 2012. Based on load impacts for a typical event day in a 1-in-2 weather year, the aggregate load impact estimated for 2012 would equal about 122 MW. Using 1-in-10 year weather, which is more appropriate for valuing demand resources because it represents the conditions under which the resource is more likely to be called and to provide its greatest value, the 2012 typical event day value equals 159 MW. On the system peak day in a 1-in-10 year, the aggregate impact is 178 MW.

Table 1-4
Residential SmartAC Aggregate Load Impact Estimates (MW)
By Weather Year, Forecast Year and Day Type
(Event Period 2-6 PM)

Weather Year	DAY TYPE	2010	2011	2012-2020
1-in-2	Typical Peak Day	87.9	112.3	122.4
	May Peak Day	19.7	27.5	32.0
	June Peak Day	54.7	70.5	78.3
	July Peak Day	121.2	157.9	173.2
	August Peak Day	84.8	106.0	113.1
	September Peak Day	70.8	89.7	94.5
	October Peak	10.3	13.1	13.6
1-in-10	Typical Peak Day	112.0	145.2	159.0
	May Peak Day	64.3	85.7	98.1
	June Peak Day	97.6	127.2	142.0
	July Peak Day	88.8	115.8	127.0
	August Peak Day	126.9	165.4	178.3
	September Peak Day	83.7	106.9	112.6
	October Peak	55.4	70.4	72.9

1.4. NON-RESIDENTIAL SMARTAC LOAD IMPACT SUMMARY

From inception through 2009, PG&E did not actively market SmartAC to non-residential customers. At the end of 2009, there were roughly 1,000 non-residential customer accounts enrolled in SmartAC. PG&E is currently marketing SmartAC more aggressively to non-residential accounts. Enrollment estimates for non-residential customers were developed by The Brattle Group (TBG).[7] Enrollment is forecasted to increase to roughly 2,400 participants by early 2010 and to continue at a steady pace and reach almost 6,900 by the end of 2011. It is assumed to stay at that level from 2012 through 2020.

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[7] Joe Wharton, Ph.D., Armando Levy, Ph.D., Doug Mitarotonda, Ph.D., Sean Ogden, and Jenny Palmer (The Brattle Group, LLC) and Bruce Perlstein, Ph.D. (Strategy, Finance & Economics, LLC), *The 2010 – 2020 Enrollment Forecasts for PG&E's Demand Response Programs for Non-Residential Customers* (April 1, 2010).

Table 1-5 shows the program-specific aggregate load impact estimates for the non-residential SmartAC program for each monthly system peak day based on each weather year and all forecast years in which enrollment changes substantially. As seen, the total load reduction for this customer segment is expected to grow from roughly 2 MW to 6 MW over the next two years and then hold steady over the forecast horizon.

Table 1-5
Non-Residential SmartAC Aggregate Load Impact Estimates (MW)
by Weather Year, Forecast Year and Day Type
(Event Period 2-6 PM)

Weather Year	Day Type	Year		
		2010	2011	2012-2020
1-in-2	May Peak Day	2.05	4.12	5.59
	June Peak Day	2.16	4.30	5.52
	July Peak Day	2.56	5.05	6.14
	August Peak Day	2.68	5.24	6.08
	September Peak Day	2.73	5.27	5.80
	October Peak Day	2.41	4.56	4.78
1-in-10	May Peak Day	1.99	4.01	5.44
	June Peak Day	2.23	4.45	5.73
	July Peak Day	2.17	4.30	5.24
	August Peak Day	2.38	4.64	5.36
	September Peak Day	2.71	5.22	5.74
	October Peak Day	2.83	5.42	5.68

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2. INTRODUCTION

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- Residential SmartRate™,[8] in both its current form as well as in a revised structure, referred to here as Peak Day Pricing (PDP), that will replace SmartRate starting in 2011;
- Residential time-of-use (TOU) tariffs E-6 and E-7;
- The SmartAC™ program for residential and non-residential customers.

This volume documents the ex ante analysis and results for the above programs and tariffs for 2010 through 2020. Ex post impacts for 2009 are presented in Volume 1. The load impact estimates presented here are intended to conform to the CPUC Load Impact Protocols.[9]

The remainder of this section contains a brief overview of each tariff and program listed above. A more detailed discussion of the historical perspective and current enrollment in each program is contained in Volume 1. The discussion below focuses on aspects of the programs and tariffs that are pertinent to development of the enrollment forecasts and ex ante load impact estimates that are presented later in this report. The ex-ante impacts are designed to describe the load reduction capability of the program under a standard set of weather conditions, accounting for projected changes in enrollment and customer mix.

2.1. SMART RATE/PEAK DAY PRICING OVERVIEW

In May, 2008, PG&E began offering a critical peak pricing tariff known as SmartRate to residential and small commercial customers in the Bakersfield and greater Kern County area. This region was the first in PG&E's service territory to receive new meters under the Company's advanced metering infrastructure deployment, branded as the SmartMeter™ Program. By the end of the 2008 program year, enrollment in the Kern County area exceeded 10,000 customers. SmartRate marketing was suspended from the fall of 2008 through early spring 2009. Starting in May 2009, enrollment expanded both in terms of the number of customers and the geographic regions covered. At the beginning of the 2009 program season, roughly 8,500 residential customers were enrolled in the program and by the end of September 2009, more than 22,000 customers were enrolled. At the time this report was written, active enrollment equaled approximately 25,500 customers.

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[8] Any use of the term SmartMeter, SmartRate or SmartAC in this document is intended to refer to the trademarked term, whether or not TM is included. SmartMeter™ is a trademark of SmartSynch, Inc. and is used by permission.

[9] Attachment A to CPUC D.08-04-050 issued on April 28, 2008. Hereafter referred to as the Load Impact Protocols.

PG&E will continue to market SmartRate to residential customers through the first half of 2010, targeting high-use, high-response customers.[10] PG&E expects to enroll an additional 35,000 customers by early summer of 2010.

Based on the February 25, 2010 decision on PG&E's Peak Day Pricing filing,[11] SmartRate will no longer be available starting in 2011. The ex ante enrollment forecasts presented here are based on the key elements contained in that decision, which include:

- The current SmartRate option available to residential customers will remain in effect until February 2011, at which time SmartRate customers will be moved to the new residential PDP rate unless the customer opts out to a non-time differentiated residential tiered.
- There will be between 9 and 15 PDP event days per calendar year.
- All customers that are defaulted to, or choose, the PDP rate will be afforded bill protection for the first year, unless they choose to wave such protection. This provision means that customers will be billed at the lower of their bill calculated based on the PDP tariff and based on the otherwise applicable tariff (typically E1).
- All Customers subject to PDP will have a hedging option to reduce bill volatility. For residential customers, this option will give each participant the option of facing PDP prices on every PDP event day, or on alternating event days.
- Customers who are on the PDP rate may opt out any time during the first year. After the first year, customers can be limited to switching rate schedules once a year.
- The Alternative 1 residential PDP proposal by PG&E is the most reasonable.

With regard to this latter point, PG&E proposed two PDP rate options. The adopted rate is an overlay on tariff E1 and has a relatively high peak period price on PDP days and a very small price differential between peak and off-peak prices on other weekdays. Since the underlying E-1 tariff is a five-tier, increasing block rate, the average price during the peak period on PDP days will vary across customers based on consumption.[12] Table 2-1 compares the average peak-period price for a customer on the PDP tariff compared with the E-1 rate.

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[10] Section 3 of this report discusses analysis that identifies high use, high response customers for SmartRate and SmartAC. This information was provided to PG&E's SmartRate marketing group and the 2010 campaign is targeting these high value customers.
[11] CPUC Decision 10-02-032. Decision on Peak Day Pricing for Pacific Gas and Electric Company. February 25, 2010 (Issued 3/2/10). A 09-02-022
[12] The number of kWh associated with each tier varies with climate zone.

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Table 2-1
Average Price by Rate Period and Tier for Residential Peak Day Pricing Customers (Prices Based on Mid-Tier Energy Use)

Tier	E-1 (¢/kWh)	Peak Period Price (¢/kWh)	Peak Period Price Ratio (PDP/E1)
1	11.5	61.6	5.4
2	11.7	61.8	5.3
3	14.9	65,0	4.4
4	21	73.6	3.5
5	26.7	85.5	3.2

2.2. TOU TARIFF OVERVIEW

PG&E has had a traditional TOU tariff in place for many years. The E-7 tariff is a two-period, five-tier tariff. The peak period for the E7 tariff is from noon to 6 pm on weekdays, with off-peak prices in effect at all other times. The peak period is the same the entire year. The E7 rate has been closed to new customers since 2007. It was replaced by the E-6 tariff, which is a three-period, five-tier TOU rate. With the E6 tariff, the peak period is from 1 pm to 7 pm in the summer months. The partial peak period in the summer is from 10 am to 1 pm and 7 pm to 9 pm, Monday through Friday and from 5 pm to 8 pm on Saturdays and Sundays. In the winter, peak period prices do not apply, and partial peak prices occur from 5 pm to 8 pm on weekdays only. There are two versions of each rate, one for CARE customers and one for non-CARE customers. Table 2-2 shows the electricity price by rate period for E-6 and E-7 customers.

At the end of 2009, there were approximately 85,000 customers being served under the four versions of PG&E's TOU tariffs, with almost 78,000 on E7 and 7,410 on E6. About 8% of the E7 customers were on the CARE tariff and about 4% of E6 customers were CARE customers. A detailed breakdown of E6 and E7 customers by local capacity area and between standard and net metered customers is contained in Section 2 of Volume 1.

Table 2-2
E-6 and E-7 Prices[13]

Rate	Rate Description	Minimum Charge (cents)	Meter Charge (cents per meter per day)	Season	TOU Period	Energy Charge (¢/kWh) Tier 1 (baseline)	Tier 2 (101-130% of baseline)	Tier 3 (131-200% of baseline)	Tier 4 (201-300% of baseline)	Tier 5 (300% of baseline+)	Average total rate (c/kWh)
E7	Residential time-of-use (4 periods)	14.8	11.5	Summer	Peak	28.1	29.7	42.6	54.5	60.8	18.5
					Off-Peak	7.1	8.7	21.6	33.5	39.8	
				Winter	Peak	10.0	11.6	24.5	36.4	42.6	
					Off-Peak	7.4	9.0	21.9	33.9	40.1	
EL-7	Residential time-of-use, Care (4 periods)	14.8	0.0	Summer	Peak	26.8	26.8	26.8	26.8	26.8	8.7
					Off-Peak	6.1	6.1	6.1	6.1	6.1	
				Winter	Peak	8.9	8.9	8.9	8.9	8.9	
					Off-Peak	6.4	6.4	6.4	6.4	6.4	
E6	Residential time-of-use (6 periods)	14.8	25.3	Summer	Peak	29.3	30.8	43.7	55.6	61.7	17.9
					Part-Peak	14.4	16.0	28.9	40.7	47.0	
					Off-Peak	8.4	10.0	22.9	34.8	41.0	
				Winter	Peak	10.0	11.6	24.4	36.3	42.5	
					Off-Peak	8.8	10.4	23.3	35.2	41.4	
EL-6	Residential time-of-use, Care (6 periods)	11.8	20.2	Summer	Peak	20.8	22.0	22.0	22.0	22.0	8.7
					Part-Peak	10.2	11.5	11.5	11.5	11.5	
					Off-Peak	6.0	7.2	7.2	7.2	7.2	
				Winter	Peak	7.1	8.3	8.3	8.3	8.3	
					Off-Peak	6.2	7.5	7.5	7.5	7.5	

2.3. RESIDENTIAL SMARTAC PROGRAM OVERVIEW

PG&E's SmartAC™ program involves the installation of programmable communicating thermostats (PCTs) and/or direct load control switches (switches) in households and small/medium businesses with central air conditioning. The control devices allow air conditioning equipment to be cycled or thermostats to be adjusted[14] when an event is triggered, thereby reducing energy demand associated with air conditioning load. SmartAC events can only be called under emergency or in anticipation of emergency conditions between May 1st and October 31st and for an event period of six hours or less for no more than 100 hours per season.

PG&E began marketing the SmartAC program in early 2007. Most marketing has been done using direct mail. To date, most residential participants were paid a one-time fee of $25 to allow installation of one or more devices at their premise.[15] In August 2009, PG&E submitted a request

[13] http://www.pge.com/nots/rates/tariffs/electric.shtml#RESELEC_TOU
[14] Air conditioner cycling can be done with either load control devices or thermostats, while thermostats can also be used to reduce air conditioning use by adjusting temperature settings.
[15] Some of the methods being tested are also described in PG&E's *SmartAC 2009 Annual Report*, December 31, 2009.

to the CPUC to modify the goals and budgets for SmartAC.[16] In its application, PG&E proposed 1) Improving the cost effectiveness of the program by primarily targeting the population of customers equipped with central air conditioning in hotter climate zones with high air conditioning loads, thereby minimizing enrollment of eligible customers in cooler climate zones with low air conditioning loads; 2) Reducing the target number of installed active devices to reflect better understanding of what is achievable by the end of 2011; 3) Obtaining an estimated 219.9MW[17] of peak load savings (1-in-10 year weather) based on installing approximately 269,000 total devices by December 2011; and, 4) Decreasing the currently adopted budget from $179 million to $123 million over the 5-year program cycle (2007-2011).

2.4. NON-RESIDENTIAL SMARTAC PROGRAM OVERVIEW

From program inception through 2009, PG&E has not actively marketed SmartAC to non-residential customers. At the end of 2009, there were roughly 1,000 non-residential customer accounts enrolled in SmartAC. On average, each account had approximately 2.5 control devices (mostly PCTs) installed at the premise. PG&E is currently marketing SmartAC more aggressively to non-residential customers, including testing alternative marketing methods such as direct mail with telemarketing or email follow up and the use of account representatives for SMBs that are assigned accounts.

2.5. REPORT ORGANIZATION

The remainder of this report is organized as follows.

Section 3 presents analysis designed to increase marketing effectiveness through improved customer targeting. Customers with central air conditioning are not only the sole target market for SmartAC, but are also prime candidates for SmartRate and PDP, since analysis shows that customers that use central air conditioning provide larger load reductions from dynamic pricing than do customers without central air conditioning. Thus, identifying customers with a high probability of owning central air conditioning, and a high probability of using it, are important to improving marketing effectiveness and maximizing program benefits relative to costs for both SmartAC and SmartRate/PDP. Section 3 discusses models that were developed to identify customers with a high likelihood of owning and using central air conditioning. These models were used in enrollment and impact modeling for the residential SmartAC program discussed in Section 7. A model linking SmartRate load reductions to customer characteristics, including the likelihood of air conditioning ownership, is also discussed in Section 3. This model is used in the enrollment and impact estimation for SmartRate/PDP discussed in Sections 4 and 5.

Section 4 presents the enrollment projections underlying the ex ante load impacts for each tariff and program. It begins with a presentation of the choice modeling that was used to estimate enrollment for the PDP tariff. Choice models were developed based on a combination of actual choice data for SmartRate and on stated preference survey data for PDP. Enrollment estimates for SmartRate for 2010 and for SmartAC for 2010 and 2011 are based on estimates developed by

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[16] A.09-08-018, *Application of Pacific Gas and Electric Company (U 39 E) for Approval of 2010-2011 SmartAC™ Program and Budget ;Pacific Gas and Electric Company Prepared Testimony.*
[17] Represents portfolio value for the highest load hour during the event window (between 5 and 6 p.m.) on a system peak day based on 1-in-10 year weather conditions.

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PG&E's program marketing department. Section 4 also documents the enrollment projections for the TOU tariff and the residential and non-residential SmartAC programs.

Section 5 presents the ex ante load impact estimates for SmartRate for 2010 and PDP for 2011 through 2020. Estimates are presented based on 1-in-2 and 1-in-10 year weather conditions, as required by the CPUC Load Impact Protocols. The method used to determine the weather that represents 1-in-2 and 1-in-10 year conditions is different this year from the approach used in 2008. The new weather year methodology and the reasons for changing the approach are documented in Appendix C.

Section 6 presents the ex ante load impact estimates for PG&E's TOU tariffs. Sections 7 and 8 contain load impact estimates for SmartAC residential and non-residential customers, respectively. An electronic appendix is available that contains hourly load impact tables for all forecast years for each program.

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3. IDENTIFYING TARGET CUSTOMERS

As discussed in Section 2, PG&E recently designed its marketing strategy for SmartAC to target high-load customers in order to increase the average load reduction for participating customers and thus increase cost effectiveness. PG&E is also trying to improve marketing effectiveness by targeting customers with a high probability of owning central air conditioning, since air conditioning ownership is a requirement for SmartAC program participation. Sending promotional materials to consumers who do not have central air conditioning is not cost effective.

Identifying customers with a high probability of owning central air conditioning is also useful for SmartRate/PDP marketing. Customers with central air conditioning are more price responsive than those without air conditioning, and produce much larger absolute load reductions than do households without central air conditioning.[18] Central air conditioning ownership likelihood is also used as input to the model that identifies likely response to the SmartRate/PDP tariffs as a function of customer characteristics. This response rate model is used as part of the targeting strategy underlying the SmartRate/PDP enrollment and impact estimates presented in Section 5.

This section documents the development of three models that are designed to help identify high-value customers for the SmartRate and SmartAC programs. The first model, discussed in Section 3.1, predicts the likelihood of ownership of central air conditioning as a function of data that are known for all of PG&E's customers (e.g., weather variables, usage, participation in other PG&E's programs, etc.). The second model, discussed in Section 3.2, predicts peak-period energy use as a function of ownership propensity and other observable variables. Validation checks indicate that both models do an excellent job of identifying high value customers. Section 3.3 combines the ownership and usage models to produce average and aggregate estimates of air conditioning usage on high system load days by LCA. Section 3.4 documents a model that estimates the likely load reduction that would be provided by customers on time-varying rates as a function of customer characteristics, including the likelihood of air conditioning ownership. Output from this model is used to target customers for enrollment into the SmartRate/PDP tariff.

3.1. MODEL OF PROBABILITY OF CENTRAL AIR CONDITIONING OWNERSHIP

In order to estimate the probability of central air conditioning ownership, it is necessary to have air conditioning ownership data for a sample of customers. The customer sample used to estimate air conditioning ownership was taken from the 2003 Residential Appliance Saturation Survey (RASS) for the PG&E service territory. Using data on customer characteristics available for the PG&E population at large, a "Probit" model of the probability of having central air conditioning was estimated for the RASS sample. The resulting coefficients of the estimated model were then applied to the full PG&E population, resulting in an estimated probability of central air-conditioning for each customer in PG&E's service territory.

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[18] As is seen later, households with central air conditioning are less likely to participate in time varying rate programs because electricity prices are higher at times when air conditioning use is most valued and household loads are high.

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3.1.1. Central Air Conditioning Database

The 2003 RASS was sponsored by five utilities, including PG&E. It includes data on the presence of central air-conditioning in each household surveyed. The survey was performed by mail, with additional telephone and in-person interviews done on a sample of non-responders. The sample is well-suited for developing a model of central air conditioning ownership because it is a stratified random sample from the PG&E population.[19] The RASS dataset contains central air conditioning data on 8,542 unique residential Service Account IDs (SAIDs).[20]

The RASS is from 2003, which means that some SAIDs have changed since the survey was done and would not match up with current PG&E customer data. Matching RASS data with current PG&E data left 5,711 SAIDs. The PG&E data that was combined with the RASS data included climate zone, nearest weather station (in order to assign hourly temperature data to each customer), address, monthly billing data (including usage) from June 2007 through September 2009, CARE status and energy efficiency rebate status (see below for explanations of both).

In order to capture variation in demographic characteristics, census data were obtained for each census block group (CBG) within PG&E's service territory. A CBG is a geographical unit used by the United States Census Bureau. It is smaller than a census tract and larger than a census block. A CBG is the smallest geographical unit for which the bureau publishes sample data (i.e. data collected from a fraction of all households rather than from all households). CBGs generally contain between 600 and 3,000 people, with an optimal size of 1,500 people. California has a total of 22,133 CBGs, of which approximately 7,686 are in PG&E's service territory. The database includes a variety of potentially useful information about customers in a CBG. A third-party vendor provided census block group mapping for each PG&E customer based on address. This mapping was successful for over 97% of SAIDs. Using this mapping as a link to the US census, FSC added census data such as the median house age within block group, and the median household income within block group to the database. The final estimation database, including PG&E customer information and census information, has information on 5,566 SAIDs.

Table 3-1 shows the total number of customers in the database that are located in each of the four primary climate zones in PG&E's service territory, and how many have central air conditioning. Central air conditioning ownership varies from a low of 3% in zone T, the cool coastal zone where fog is prevalent in the summer time, to a high of 63% in zone S, the hot inland valley where 100 degree days are common in the summer.

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[19] Stratification variables were age of home, presence of electric heat, home type, and climate zone. For more information on the RASS, see http://www.energy.ca.gov/appliances/rass/ .

[20] In this report, SAID and customer are used interchangeably, even though they are not identical within PG&E's information systems. However, for residential customers, at any point in time, there is close to a one-to-one correspondence between customers and SAIDs.

Table 3-1
Number of Customers in 2003 Residential Appliance Saturation Survey that Own Central Air Conditioning by Climate Zone

Climate Zone	No CAC	CAC	Total	% Ownership
R	333	455	788	58%
S	416	707	1123	63%
T	1430	46	1476	3%
X	1386	793	2179	36%
Total	**3565**	**2001**	**5566**	**36%**

3.1.2. Probability Model

A Probit specification was used to model the likelihood of central air-conditioning ownership. A Probit is a type of regression that is well-suited to modeling "yes/no" variables. In this case, the "yes/no" variable was an indicator of central air conditioning ownership. As described below, this dependent variable was modeled as a function of several independent variables. A number of combinations of variables were tested before settling on the final model specification. The variables examined for inclusion were:

- CARE Status—CARE stands for California Alternate Rates for Energy and is a program through which enrolled, low income consumers receive lower rates than non-CARE customers;
- Whether a customer had previously received a rebate or some other form of incentive through one of PG&E's energy efficiency (EE) programs from 2003 through 2008. Although not all of these rebates pertain to central air conditioning, two of the most common ones do. As such, it is reasonable to expect that there would be a positive correlation between EE rebates and air conditioning ownership;
- The logarithm of median household income in the CBG;
- The median age of houses in the CBG;
- Average number of people per household in the CBG;
- Median age of CBG population;
- Fractions of population in the CBG who are black, white, and Asian;
- Number of households with children under 18 in the CBG;
- Number of one-person households and number of two-person households in the CBG;
- Several location variables: climate zone (10 zones), climate zone (4 zones), local capacity area, and nearest weather station;

- The correlation between monthly cooling degree hours[21] (with a base temperature of 70; referred to as CDH70) and monthly usage (in kWh) for a given customer for June 2007 through September 2009. The logic behind including this variable is that if a customer's usage is strongly correlated with high temperatures, then it is likely due to the presence of an air-conditioner;

- The correlation between monthly cooling degree hours (with a base temperature of 80) and monthly usage (in kWh) for a given customer for June 2007 through September 2009;

- The correlation between monthly cooling degree days (with a base temperature of 65) and monthly usage (in kWh) for a given customer for June 2007 through September 2009;

- Several interactions between location variables and income, house age variables, correlation variables and population race variables.

The final model included as independent variables the correlation between CDH70 and monthly usage, CARE status, EE rebate status, location variables indicating the nearest weather station, and indicators for the four climate zones interacted with two census variables: the logarithm of median household income in the CBG; and the median age of houses in the block group.

Table 3-2 contains average values by climate zone for the correlation between CDH70 and monthly usage, CARE status, EE rebate status, house age and income in the sample population. The correlation between CDH70 and monthly usage is highest, on average, in zones R and S (0.47 and 0.25 respectively). In zones T and X, the average correlations are negative (-0.34 and -0.18, respectively). These correlations are for the whole year, not just the summer period. The penetration of air conditioning is extremely low in zone T and the high, negative correlation in this zone reflects a behavioral pattern unrelated to air conditioning. For example, it may be that as CDH increases in this very moderate climate region, people spend more time outdoors and use less electricity as a result. A similar explanation could be true in much of zone X, where temperatures are quite mild and air conditioning use is rare. The proportion of CARE customers varies by more than a factor of two, from a low of 0.12 in zone X to a high of 0.28 in zone R. The proportion of customers receiving an energy efficiency rebate varies from 0.20 in zone T to 0.34 in both zones X and S. House age varies from a low of 29 years in zone S to a high of 49 years in zone T, reflecting the much more rapid growth in the last several decades in the hotter regions relative to the Bay Area.[22] This inland migration and growth can also be seen in the fact that the saturation of central air conditioning shown in Table 3-1 is inversely correlated with household age across climate zones. As we will see below, house age is a highly significant predictor of CAC. Finally, average CBG income varies from a low of $54,000 in zone R to a high of $92,000 in zone X.

[21] Monthly cooling degree hours are measured by subtracting the base temperature from the hourly average temperature, and adding those up for every hour in the month. If the average temperature for an hour is below the base temperature, cooling degrees for that hour equal zero. Cooling degree days are calculated similarly, but using daily average temperature.
[22] Values for house age and household income are means over climate zones of median values within census block groups.

Table 3-2
Selected Statistics for RASS Households[23]

Climate Zone	Correlation between CDH70 and Usage	% CARE Customers	% EE Rebate Customers	House Age	Household Income ($ 1000s)
R	0.47	28%	28%	30.5	53.8
S	0.25	20%	34%	29.4	63.9
T	-0.34	17%	20%	48.5	73.7
X	-0.18	12%	34%	38.1	92.0
Total	**-0.04**	**17%**	**30%**	**38.1**	**76.0**

Table 3-3 shows coefficient values, standard errors, marginal effect sizes, and diagnostics for the air conditioning likelihood model. The value in the marginal effect column represents the change in the probability that a household owns a central air conditioner given a small change in the value of the variable. Both income and house age are strong predictors of central air conditioning probability. In each zone, the marginal effect coefficient for "log(median income)" is close to 15%. This means that a 1% increase in median income leads to a 0.15% increase in the probability of central air conditioning ownership.[24] Also, an increase of one year in median house age leads to a 0.8% decrease of the probability of owning a central air conditioner in zone X and a 0.5% decrease in zone R. In zone T, it appears that there is no relationship between central air conditioner ownership and house age, which is not surprising given the very low saturation of central air conditioning in that zone.

The correlation between CDH70 and monthly usage is also a strong predictor. A 1% increase in that correlation leads to a 0.2% increase in the probability of owning central air conditioning. We tested models in which this effect was allowed to vary across climate zones, but that did not yield greater predictive accuracy.

CARE status and EE Rebate are both "yes/no" variables. A CARE customer has a 7.6 percentage point smaller probability of having CAC than a similar non-CARE customer. A customer who has received an EE rebate is 9.8 percentage points more likely to have central air conditioning than a similar customer who has not received a rebate.

[23] Values for house age and household income are means over climate zones of medians within census block groups

[24] An increase of 0.01 in log(median income) is approximately equal to a 1% change in median income.

Table 3-3
Probit Model Coefficients for Probability of Owning Central Air Conditioning

Independent Variables	Coefficient	Standard Error	P-value	Marginal Effect
zone R x log (median income)	0.42	-0.067	0.00	0.14
zone R x Median House Age	-0.01	-0.004	0.00	0.00
zone S x log (median income)	0.46	-0.065	0.00	0.15
zone S x Median House Age	-0.02	-0.003	0.00	-0.01
zone T x log (median income)	0.37	-0.068	0.00	0.12
zone T x Median House Age	-0.01	-0.005	0.09	0.00
zone X x log (median income)	0.49	-0.064	0.00	0.17
zone X x Median House Age	-0.02	-0.003	0.00	-0.01
Correlation(CDH70, usage)	0.62	-0.043	0.00	0.21
CARE	-0.24	-0.059	0.00	-0.08
EE Rebate	0.28	-0.046	0.00	0.10
Constant	-4.51	-0.732	0.00	
Observations	**5566**			
Pseudo R-square	**0.35**			
Chi-square p-value	**0.00**			
Log-likelihood	**-2355.00**			

Two simple diagnostic measures are also shown in Table 3-3. Pseudo-R-squared[25] is an indicator of how much explanatory power the variables provide, as compared to simply assuming an average value for everyone. In this case, pseudo-R-squared equals 35%, which indicates a substantial improvement over assuming an average value for the probability of owning central air conditioning for all customers. The p-value of the chi-square statistic is less than 0.01%, which means that the relationships in the estimated model are very unlikely to be due to random chance.

As a method of assessing the appropriateness of various models, models were estimated using data from one half of the sample and then used to predict the likelihood of central air conditioning ownership for households in the other half of the sample.[26] This test indicates how the model should perform in out-of-sample prediction on the entire PG&E population. Figure 3-1 compares the actual rate of central air conditioning ownership to out-of-sample predictions on half the sample, by local capacity area (LCA). As the figure shows, the model performs well across local capacity areas in out-of-sample predictions. The largest error rate is in Humboldt, which has a very low rate of air conditioning ownership. In that LCA, the model predicts air conditioning ownership equal to 2.2%, while ownership among the remaining RASS sample was actually zero. The next largest error rate is in Kern, where the model under-predicts by 5.2 percentage points.

[25] Equal to one minus the ratio of the log-likelihood of the full model to the log-likelihood of the model estimated with only a constant as an independent variable
[26] Each half was chosen by selecting a random sample of half of the customers in each climate zone (4 zones) in order to ensure coverage of each zone.

Figure 3-1
Percent of Population Owning Central Air Conditioning by LCA
Predicted versus Actual

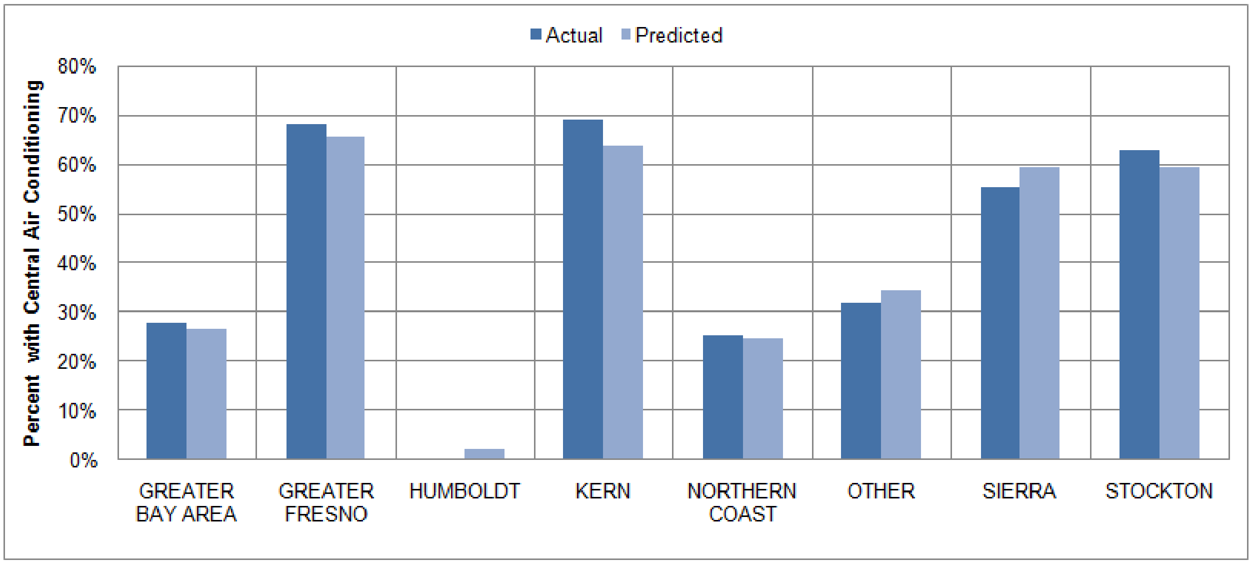
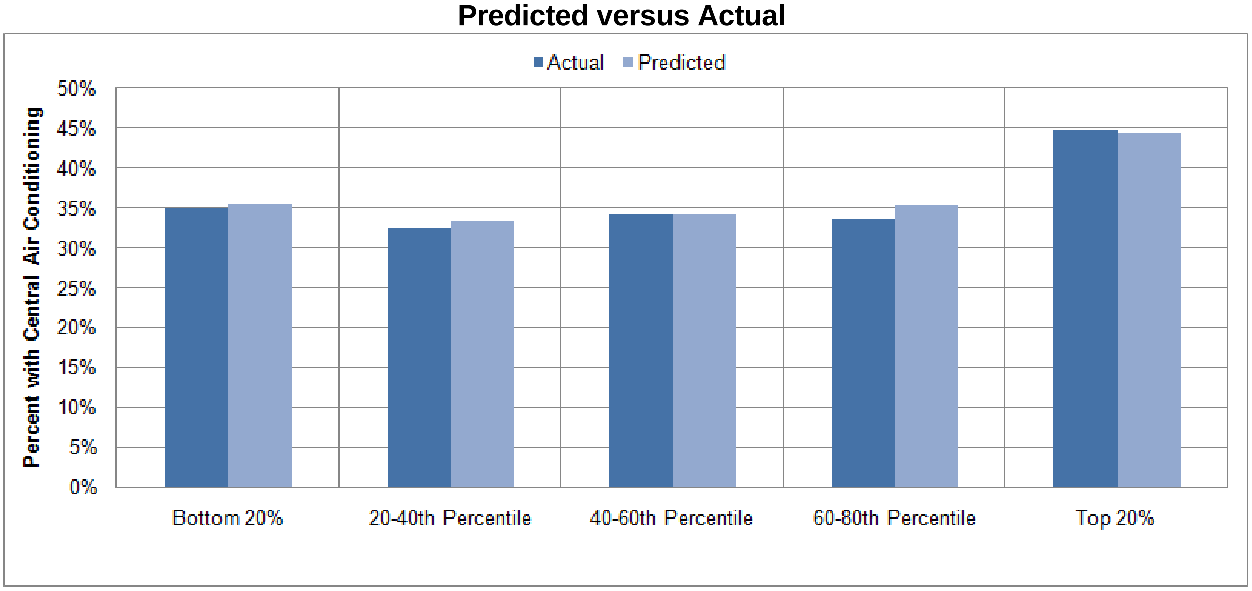


Figure 3-2 compares the actual rate of air conditioning ownership to out-of-sample predictions on half the sample, by quintile of block group median income.[27] Again, the model performs well—only the error rate for the fourth quintile is above 5% of actual ownership. In that case the error rate is 5.1%.

Figure 3-2
Percent of Population Owning Central Air Conditioning by Income Quintile
Predicted versus Actual



[27] The quintiles are composed of incomes in the ranges (in $1000s) 10-48, 48-62, 62-79, 79-100, 100-440.

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3.1.3. Model Applied to PG&E Population

The air conditioning likelihood model shown in Table 3-3 was used to assign a value to each of PG&E's 4.5 million residential customers representing the likelihood that a customer has central air conditioning. When aggregated by LCA, the average likelihood values provide an estimate of the central air conditioning saturation in each LCA. Table 3-4 shows the total number of customers in each LCA, the total number and percentage for which there was sufficient information to use the model to predict air conditioning ownership likelihood, and the predicted air conditioning saturation and number of households with air conditioning by LCA. Across all LCAs, the saturation of air conditioning is estimated to equal 37%. Values by local capacity area range from 5% in Humboldt to 66% in Stockton. Overall, the air conditioning likelihood was estimated for 99% of the PG&E population. The estimated saturation of air conditioning by climate zone is 3% for zone T, 35% for zone X, 58% for zone R and 65% for zone S.

Table 3-4
Estimated Saturation of Central Air Conditioning by LCA
Based on Probability of Ownership Model

Local Capacity Area	Total Customers	Customers with CAC Probability	% Coverage of probability prediction	CAC Fraction	Expected CAC
Greater Bay Area	2,040,280	2,024,521	99%	0.27	552,100
Greater Fresno	459,874	452,871	98%	0.63	288,157
Humboldt	56,560	55,986	99%	0.05	2,760
Kern	174,091	171,275	98%	0.65	112,968
Northern Coast	461,710	458,009	99%	0.24	111,041
Other	822,387	813,363	99%	0.36	300,416
Sierra	260,843	258,324	99%	0.61	159,297
Stockton	213,259	210,448	99%	0.66	140,559
Total	**4,489,004**	**4,450,078**	**99%**	**0.37**	**1,658,238**

3.2. PEAK DAY AIR CONDITIONING LOAD MODEL

Not only is it important to determine the likelihood that customers own air conditioning, it is also important to estimate the average air conditioning load for customers on high system load days. Given the diversity of climate in the PG&E service territory, even on high system load days, not all air conditioners are in use and, for those that are, there is significant variation in average load. For marketing purposes and to maximize the cost effectiveness of SmartAC and SmartRate programs, it is useful to identify not only customers with a high propensity of owning air conditioning, but also high users among the population of air conditioner owners. This section presents a model that estimates average air conditioning usage during peak periods on high system load days for customers who own air conditioners.

A model of residential customer air-conditioning load was estimated for PG&E's five highest load days between March and August 2009.[28] The dependent variable consists of average load per customer (kW) during the 2 pm-6 pm period on those five days. The estimating sample consisted of customers in the 2009 SmartAC M&E sample[29] as well as customers included in a sample that was used to test the feasibility of using air conditioning load control as an ancillary service.[30] In total, end use logger data was collected for 705 air conditioning units from 656 individual residential SAIDs.[31] These data were combined with a variety of data for variables very similar to those used for the air conditioning ownership model documented in the previous sections.

For those customers in the sample, air conditioning load during the 2 to 6 pm time period was averaged over the top five system load days. Figure 3-3 shows the distribution of this variable. A notable aspect of the distribution is that 13% of the observations equal zero. A useful way to describe this data is "censored." Censoring takes place when a variable has a value that it cannot go below (or exceed in other cases)—called the censoring point. A standard technique for modeling censored data is the Tobit regression, which we use in this case. In this type of model, we posit an unobserved "AC load demand" function that can be positive as well as negative. We then define actual AC load as equal to "AC load demand" when "AC load demand" is greater than or equal to zero, and equal to zero when "AC load demand" is negative.[32] By assuming that "AC load demand" has a Normal (Gaussian) distribution conditional on observed covariates (and therefore actual AC load has a censored Normal distribution), we can estimate the model using standard optimization techniques.

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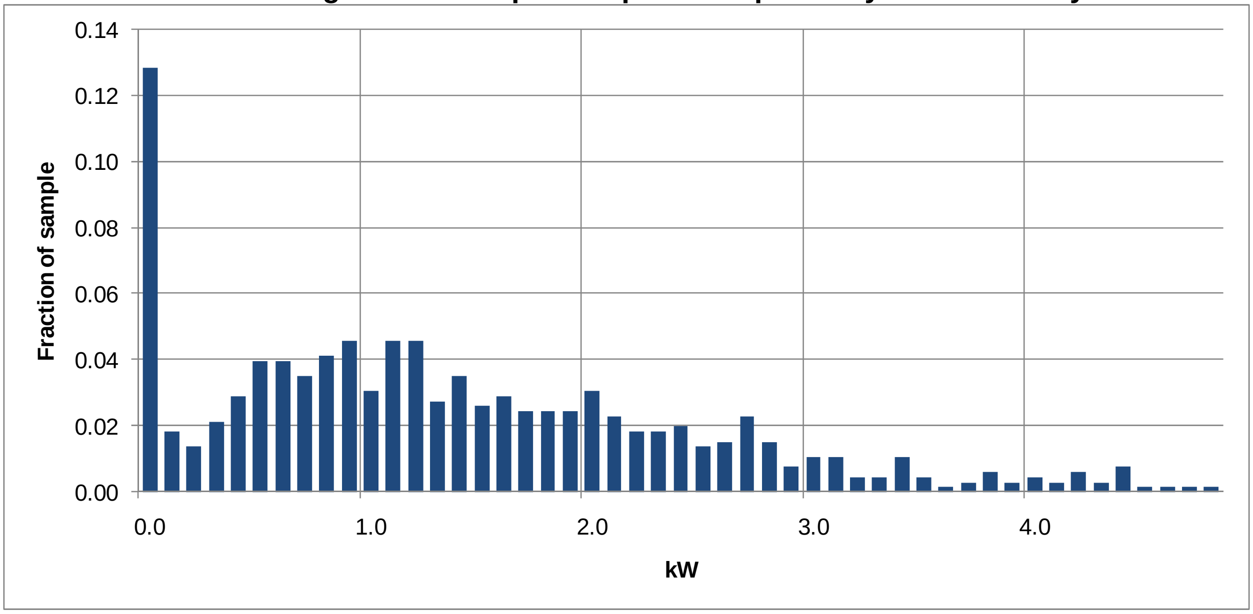
[28] June 29, July 14, 15 and 17, and August 10.
[29] See Appendix A for a summary of the SmartAC M&E load research sample.
[30] Michal Sullivan, Josh Bode and Paul Mangasarian. *2009 Pacific Gas and Electric Company SmartAC Ancillary Services Pilot.* December 31, 2009.
[31] In this report, SAID and customer are used interchangeably, even though they are not identical within PG&E's information systems. However, for residential customers, at any point in time, there is close to a one-to-one correspondence between customers and SAIDs.
[32] The idea of "AC load demand" being negative is purely a way of explaining and understanding the model. The idea is a useful tool because it allows the model to distinguish between situations where actual AC load might be positive for a very small shift in variables (e.g. perhaps the outside temperature is 75 degrees Fahrenheit) and situations where AC load would only be positive for a very large shift in variables (e.g. if the outside temperature is 35 degrees Fahrenheit).

Figure 3-3
Distribution of Average kW from 2 pm to 6 pm for Top Five System Load Days in 2009



The dependent variable was modeled as a function of several independent variables. Among the variables tested were:

- CARE status;
- Whether a customer had previously received a rebate or some other form of incentive through one of PG&E's energy efficiency (EE) programs from 2003 through September 2009;
- The logarithm of median household income in the CBG;
- The median age of houses in the CBG;
- Average temperature during the peak periods and several polynomials of average temperature;
- Average relative humidity during the peak periods and several polynomials of average relative humidity;
- The product of average temperature and average relative humidity during the peak periods and several polynomials of this product;
- Average number of people per household in the CBG;
- Median age of the CBG population;
- Median age of the houses in the CBG;
- Median household income in the CBG;

- Fractions of population in the CBG who are black, white, and Asian;
- Number of households with children under 18 in the CBG;
- Number of one-person households and number of two-person households in the CBG;
- Climate zone (four zones);
- The correlation between monthly cooling degree hours (with a base temperature of 70; referred to as CDH70) and monthly usage (in kWh) for a given customer for June 2007 through September 2009. The logic behind including this variable is that if a customer's usage is strongly correlated with high temperatures, then it is likely that they tend to use an air-conditioner more when it's hot;
- The correlation between monthly cooling degree hours (with a base temperature of 80) and monthly usage (in kWh) for a given customer for June 2007 through September 2009;
- The correlation between monthly cooling degree days (with a base temperature of 65) and monthly usage (in kWh) for a given customer for June 2007 through September 2009;
- Several interactions between climate zone and other explanatory variables.

The final model included as independent variables: the correlation between CDH70 and monthly usage; indicator variables for climate zones (which account for different weather, as well as other differences in AC load between climate zones); CARE status; and EE rebate status. The model also included indicators for the three climate zones interacted with four census variables: the median age of the population in the CBG; the average size of households in the CBG (in number of people); and the population sizes of whites, blacks and Asians in the CBG.

Note that temperature and relative humidity are not in the final model. These variables provided very little explanatory power. Most likely, this is because only times that are very hot were included in the estimating sample. Within those times, the cross-sectional variation in weather does not explain much difference in peak usage—particularly when indicators for climate zones are included in the model. Models were also estimated where each peak day load was entered as a separate data point for each customer. This change did not improve the predictive accuracy of the model, nor were temperature or relative humidity strong explanatory variables in these models.

Table 3-5 shows the number of observations in the sample from each climate zone and average values for the key variables in the load model. Note that climate zones R, S and X are represented, but T is not, because there are essentially no SmartAC participants in this zone. Climate zones R and S are about equally represented, with 265 and 257 observations, respectively. Climate zone X has roughly half as many observations, with 128.

Table 3-5
Average Estimating Sample Values for Explanatory Variables in the Load Model

Climate Zone	R	S	X	Total
Observations	265	257	128	650
Correlation between CDH70 and Usage	0.70	0.53	0.18	0.53
% CARE Customers	34%	19%	12%	24%
% EE Rebate Customers	55%	62%	56%	58%
Temperature (Fahrenheit)	103.4	100.3	95.5	100.6
Relative Humidity (%)	18%	17%	20%	18%
Household Income ($ 1000s)	62.1	87.5	116.1	82.8
Age of population	49.3	47.5	50.5	48.8
Fraction white	0.66	0.64	0.72	0.67
Fraction black	0.07	0.13	0.03	0.09
Fraction Asian	0.10	0.15	0.22	0.15

Table 3-6 shows the estimated coefficients and associated standard errors and p-values for the high load day model. As was true in the model used to predict air conditioning ownership likelihood, the correlation between CDH70 and monthly usage is a strong predictor of air conditioning load. In this case, a one percentage point increase in the correlation leads to 0.12 kW increase in air conditioning load.

Table 3-6
Model Coefficients for Estimating Air Conditioning on High System Load Days

Independent Variables	Coefficient	Standard Error	P-value
Correlation(CDH70, usage)	1.24	0.13	0.00
Climate zone S	-3.64	1.61	0.02
Climate zone X	-5.15	2.35	0.03
zone R x median age	0.01	0.01	0.34
zone R x average household size	0.11	0.14	0.45
zone R x fraction white	-2.92	0.66	0.00
zone R x fraction black	-3.71	1.32	0.00
zone R x fraction Asian	-4.50	1.04	0.00
zone S x median age	0.07	0.02	0.00
zone S x average household size	0.20	0.20	0.30
zone S x fraction white	-1.69	1.02	0.10
zone S x fraction black	-7.41	1.35	0.00
zone S x fraction Asian	1.57	1.23	0.20
zone X x median age	-0.01	0.02	0.61
zone X x average household size	-0.26	0.29	0.37
zone X x fraction white	5.50	2.15	0.01
zone X x fraction black	1.61	3.51	0.65
zone X x fraction Asian	4.63	2.04	0.02
CARE	-0.02	0.10	0.81
EE Rebate	-0.24	0.09	0.00
Constant	2.41	1.02	0.02
Observations	655		
Pseudo R-square	0.11		
Chi-square Statistic	228.60		

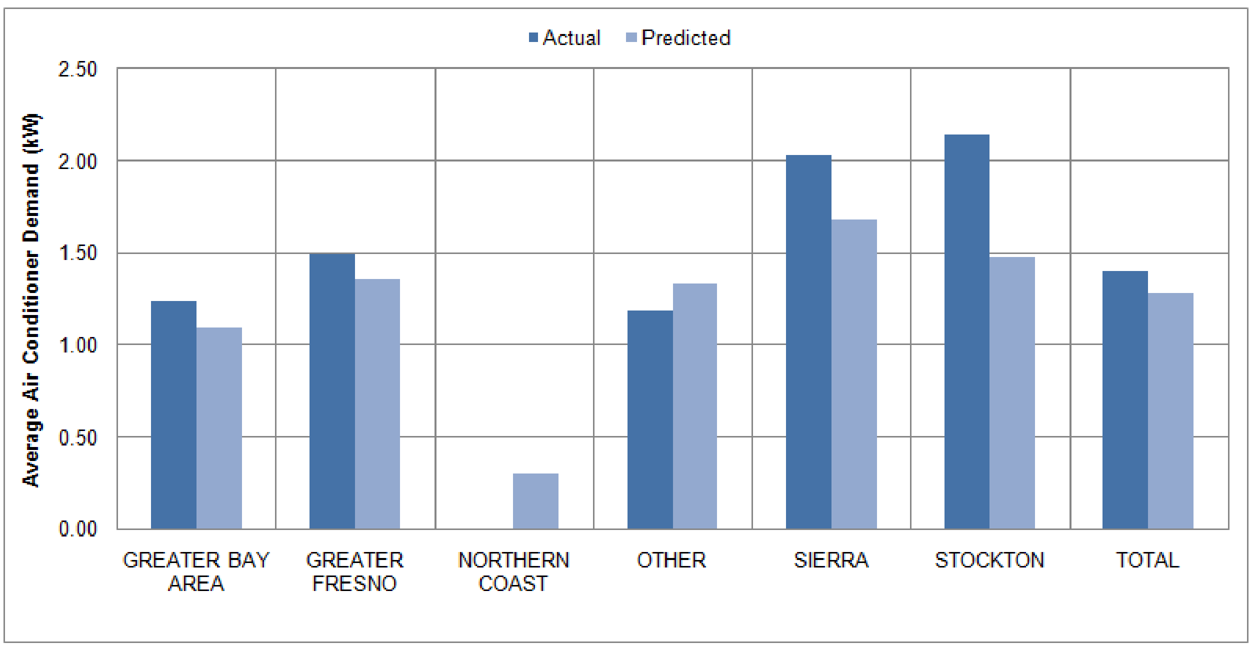
This model includes indicator variables only for zones S and X. Zone R is omitted, which means that the zone indicator variables for S and X imply differences between those zones and zone R. Interpreting the effects of these indicators is not straightforward because the indicators also enter the model interacted with demographic variables.

The coefficients of the census variables interacted with climate zone are highly variable across zones, in magnitude and statistical significance. For example, median age is highly significant in zone S, with a one-year increase in median household age leading to a 0.07 kW increase in air conditioning load. However, in zones R and X, this variable has significantly smaller magnitude and is statistically insignificant. Similarly, in zone X, the fraction of population that is white has a strong effect, with a 1% increase leading to a 0.055 kW increase in air conditioning load. However, in zones R and S, this variable is statistically insignificant.

In this model, the effect of CARE status on air conditioning load is not statistically significant. The effect of having received an energy efficiency rebate is negative and statistically significant, implying that those who have received a rebate have 0.24 kW lower air conditioning loads than those who have not.

Figure 3-4 shows the actual load for half the sample of customers compared with the predicted values based on a model estimated for the remainder of the sample. Overall, the model is quite accurate in out-of-sample prediction. The total average predicted load is 1.40 kW, versus 1.34 kW in actual average load. The largest errors, in Sierra, Stockton and the Northern Coast, are due to very small sample sizes (10, 17 and 1 customer, respectively). In the LCAs where the sample is larger, the model predicts quite well.

Figure 3-4
Average Air Conditioning Load on Top Five System Load Days
Predicted versus Actual



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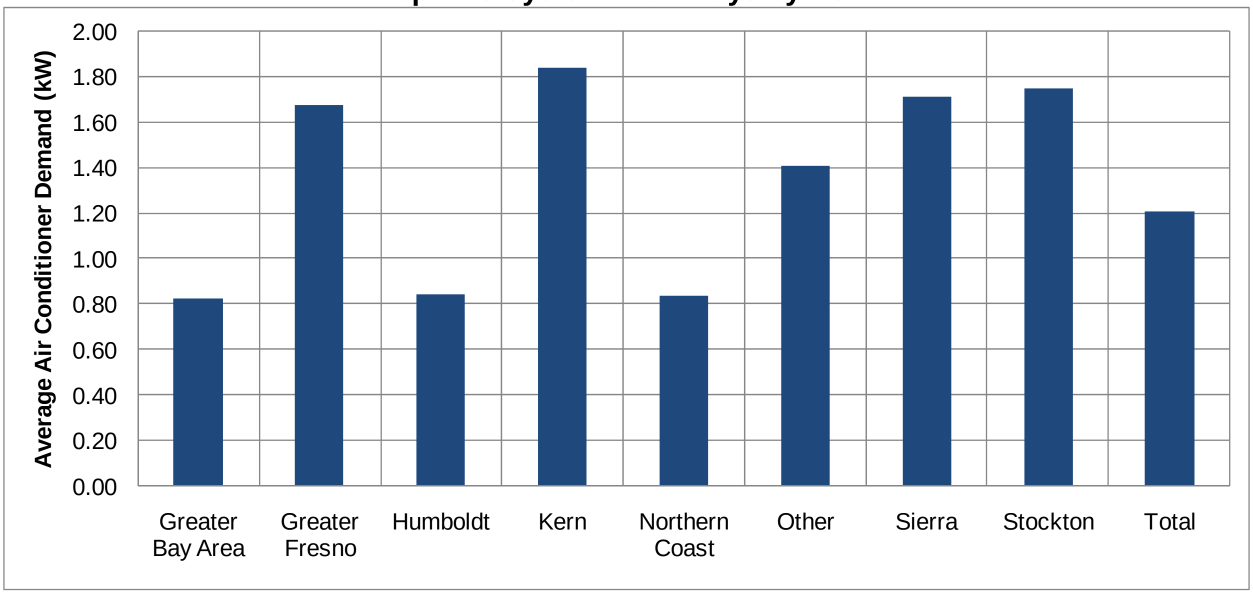
The estimated model was applied to the PG&E population as a whole.[33] The results by LCA are shown in Figure 3-5, which should be interpreted as the average AC load at peak times for households with air conditioning. The highest average is in Kern at 1.84 kW. Stockton, Sierra and Fresno all have average loads on high system load days exceeding 1.5 kW.

Figure 3-5
Average Estimated Load per Customer with Central Air Conditioning on Top Five System Load Days by LCA



3.3. COMBINING AIR CONDITIONING OWHERSHIP LIKELIHOOD WITH PREDICTED LOAD

In order to evaluate the full potential for air conditioning load demand response, it is useful to have an estimate of average and total air conditioning load among all customers on high demand days (in this instance, defined as the top five system load days). The estimated central air conditioner ownership probabilities were multiplied by the predicted air conditioning load on high system load days for each customer. This produces an average unconditional expected air conditioning load on high demand days for each customer. Because this number includes a probability estimate for each customer, it is unlikely to be an accurate reflection of actual air conditioning load for any given customer. However, when summed over customers, it should give an accurate picture of total air conditioning load at times of system peak.

Figure 3-6 shows the average expected air conditioning load by local capacity area. This is the product of the air conditioning ownership likelihood and the average air conditioning load on high demand days. Not surprisingly, the values indicate that customers in the hotter regions of Kern, Fresno, Stockton and Sierra have the highest combination of high ownership and high usage, with

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[33] Zone T was excluded for two reasons. First, there were no data points in the estimated model for zone T. Second, AC ownership and use in zone T is very low, so residential SmartAC impact in zone T is likely to be minimal.

each region having an average value exceeding 1 kW. Stockton has the highest average, at 1.24 kW, followed by Kern at 1.18 kW. The overall average is 0.71 kW (remember that this excludes all of zone T).

Figure 3-6
Average Estimated Load per Customer on Top Five System Load Days Times the Probability of Owning Central Air Conditioning by LCA

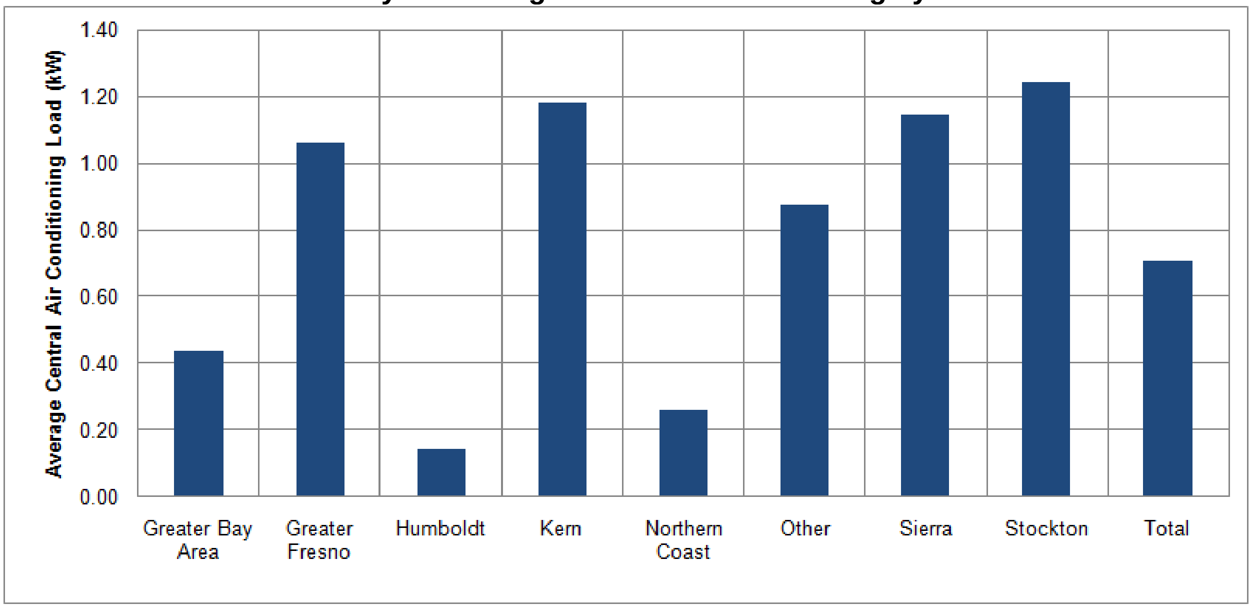
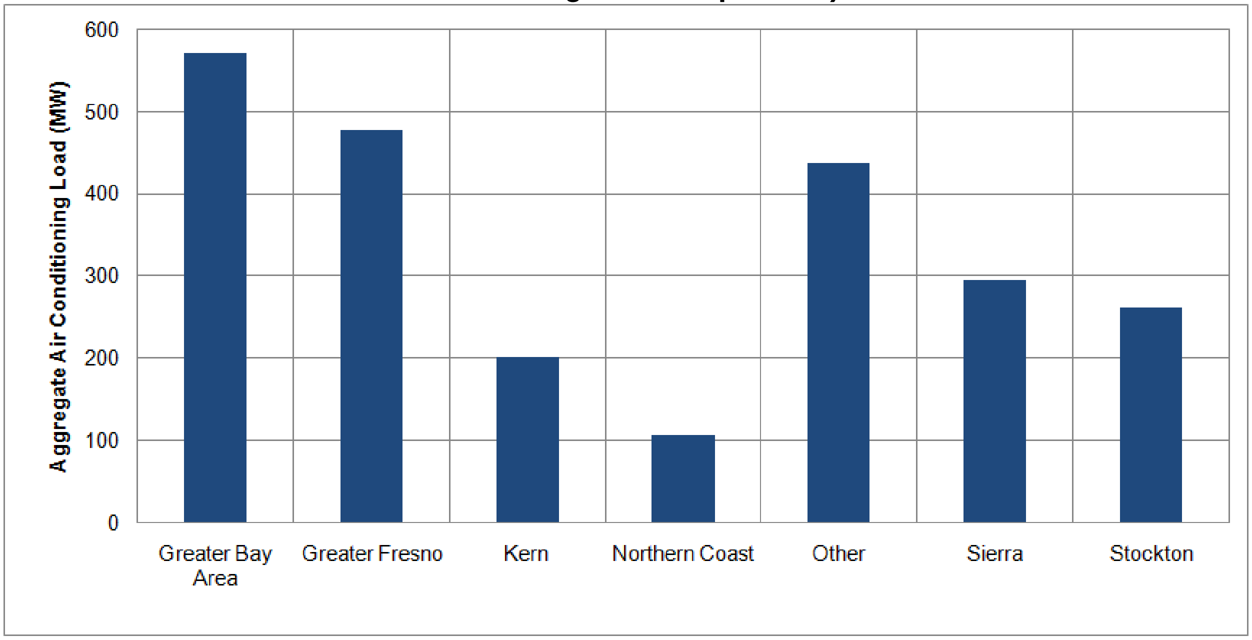


Figure 3-7 shows the overall air conditioning load potential by LCA. These values factor in the large variation in population across LCAs. The largest load potential is in the Greater Bay Area, at 570 MW, where the relatively lower average value is offset by the very large number of customers in the region. Greater Fresno is next at 480 MW. The total estimated system air conditioning load across the top five system load days is estimated to equal 2,360 MW.

Figure 3-7
Estimated Aggregate Central Air Conditioning Load on Top Five System Load Days by LCA (Average Estimated Load per Customer Times Probability of Owning Central Air Conditioning Times Population)



3.4. SMARTRATE/PDP HIGH LOAD RESPONSE MODEL

The prior models are used in developing enrollment estimates for the SmartAC program. As discussed in Section 4, enrollment modeling for SmartRate/PDP is also based on an assumed strategy that targets high value customers. The 2009 SmartRate population included a wide range of customers across regions with substantial climate and cultural differences. The individual customer load impacts were employed to estimate a predictive model of expected load impacts. Individual impact estimates were available for each event for each participant in the estimating sample.[34]

The predictive model was applied to over 4 million PG&E residential customers to identify customers that are most likely to provide large load impacts if they enroll in SmartRate/PDP. The load impact estimates were combined with individual customer estimates of enrollment likelihood, thus factoring selection into the forecast predictions.

[34] The SmartRate individual customer regression models, their validation, and results are documented in Volume 1.

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3.4.1. Regression Model Development and Description

The load impact estimates for each event day derived from individual customer regressions as described in Volume 1 were used in a second-stage regression that estimates load reduction as a function of customer characteristics. Because almost all 2009 participants experienced multiple events, impact estimates were available for each customer under different conditions.

Although individual regression estimates inherently contain measurement error, the extensive validation of results for highly price responsive customers and less responsive customers (Volume I, Section 3) indicated that there was no systematic bias in the errors. In other words, the cost of measurement error, wider confidence intervals, was far less serious than if systematic biases were embedded in the load impacts.

The model was estimated with random effects panel regression, with a correction for clustering since each customer's load response was expected to be related across events.[35] The random effects technique was employed solely because the goal of the model was to predict outside of the estimating sample. The variables from the model may or may not be robust or unbiased. As a result, we recommend strong caution in interpreting regression coefficients. The regression identifies factors that predict high load response, but those factors should not be interpreted as causal. Table 3-7 present the regression model results and parameters. Positive regression parameters indicate that the particular factor is associated with higher load response.

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[35] Typically, we strongly prefer using fixed effects over random effects for panel regressions because the technique controls for omitted time invariant variables, eliminating a key potential source of omitted variable bias. In contrast, random effect models assume that customer specific effects are unrelated to the variables in the regression – a relatively strong assumption without an empirical basis. However, the additional robustness of fixed effect models comes at a cost – it cannot be readily applied for predictive modeling. First, the fixed effects are customer specific. Second, the model absorbs customer characteristics into the fixed effects. In other words, it is not possible to use variables such as CARE status, annual consumption, or geography to predict expected load impacts for customers outside of the estimating sample.

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Table 3-7:
SmartRate High Response Predictive Regression Model Parameters

```
Random-effects GLS regression                   Number of obs      =     19297
Group variable: UNIQSPID                        Number of groups   =      1758

R-sq:  within  = 0.0634                         Obs per group: min =         2
       between = 0.2547                                        avg =      11.0
       overall = 0.2143                                        max =        15

                                (Std. Err. adjusted for clustering on UNIQSPID)
```

Variable	Coef.	Std. Err.	Z	P>z	[95% Conf.	
Number of successful notifications	0.087	0.006	13.61	0.00	0.074	0.100
CDD	0.001	0.001	0.74	0.46	-0.002	0.003
central AC likelihood x CDD	0.036	0.003	12.68	0.00	0.031	0.042
central AC likelihood x CDD x CARE	-0.012	0.003	-4.18	0.00	-0.018	-0.006
2nd year participation	0.020	0.043	0.46	0.65	-0.064	0.103
Number of events experienced in summer	-0.009	0.004	-2.64	0.01	-0.016	-0.002
2nd consecutive event	-0.002	0.010	-0.24	0.81	-0.023	0.018
Enabling tech x CDD	0.012	0.003	4.25	0.00	0.006	0.017
Annual Consumption (kWh)	0.001	0.000	4.30	0.00	0.000	0.001
Natural log of annual bill	-0.084	0.053	-1.58	0.11	-0.188	0.020
EErebate09	-0.163	0.070	-2.33	0.02	-0.300	-0.026
CARE	0.018	0.059	0.30	0.76	-0.097	0.133
Month						
June (Base)						
July	0.047	0.016	3.00	0.00	0.016	0.077
August	0.082	0.027	3.04	0.00	0.029	0.135
September	0.133	0.038	3.53	0.00	0.059	0.207
Day of week						
Monday (Base)						
Tuesday	-0.033	0.010	-3.41	0.00	-0.052	-0.014
Wednesday	-0.030	0.012	-2.50	0.01	-0.053	-0.006
Thursday	0.008	0.011	0.71	0.48	-0.014	0.030
Friday	0.038	0.021	1.78	0.08	-0.004	0.079
Climate region						
R						
S	0.056	0.047	1.20	0.23	-0.036	0.148
T	0.345	0.183	1.89	0.06	-0.012	0.703
X	0.303	0.068	4.46	0.00	0.170	0.436
Neighborhood variables						
Median home vintage	-0.003	0.001	-2.09	0.04	-0.006	0.000
median income	0.000	0.000	1.35	0.18	0.000	0.000
% of households with kids	-0.058	0.242	-0.24	0.81	-0.531	0.416
% of households with kids	0.299	0.377	0.79	0.43	-0.440	1.038
Urban density centile (census)	0.000	0.001	-0.01	0.99	-0.002	0.002
% Spanish speaking households	-0.027	0.125	-0.22	0.83	-0.272	0.217
% Homeowners	-0.232	0.150	-1.55	0.12	-0.525	0.062
Constant	5.459	2.848	1.92	0.06	-0.123	11.041

The model was applied to the PG&E residential customer population. Two of the key predictive variables were central AC likelihood and weather for event conditions. The central AC estimates were developed for the residential PG&E population as described earlier in this section. For prediction purposes, the weather conditions were estimated based on the average customer specific weather conditions for the 15 highest 2009 system load days.

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3.4.2. Model Validation

The accuracy of the model was assessed by comparing how well it predicted load impacts across different customer characteristics. Figure 4-8 reflects the ability of the model to predict for different weather conditions. Generally, the model predicts well across the range of event temperatures.

Figure 3-8:
Comparison of Predicted to Actual Load Reduction by Event Conditions

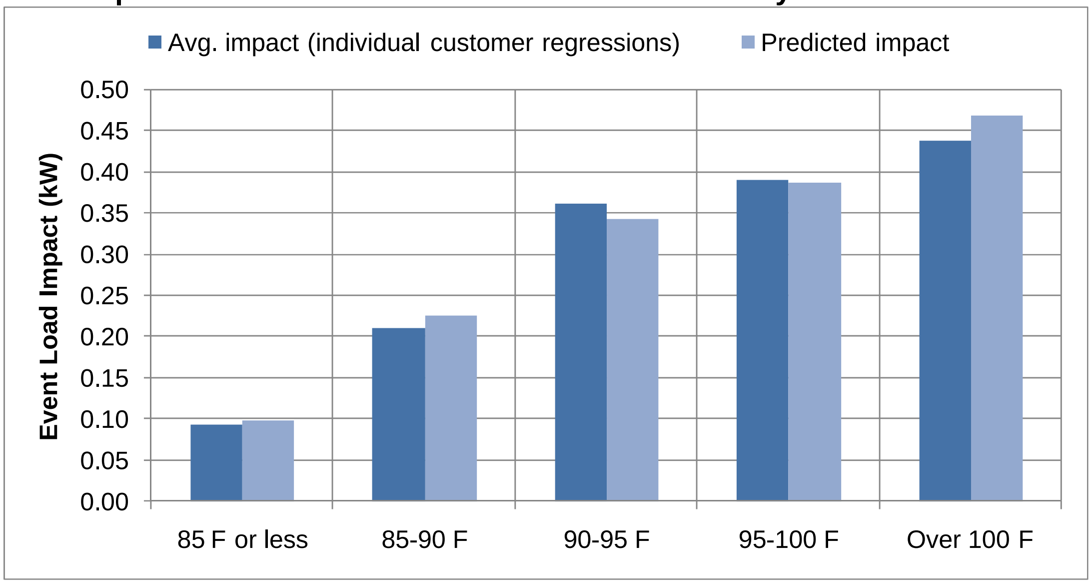
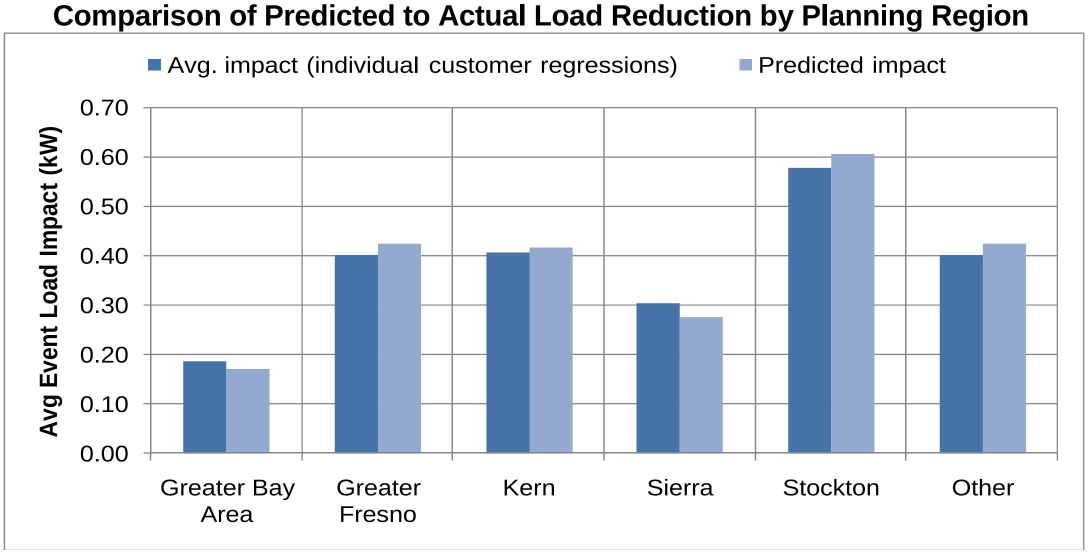


Figure 3-9 compares the predicted load impacts to the load impacts from the individual customer regressions for each planning area. The 2009 planning areas reflect the wide diversity in PG&E's service territory. The extensive coverage across the coverage is critical for accurately predicting load impacts for customers across the territory.

Figure 3-9:
Comparison of Predicted to Actual Load Reduction by Planning Region



4. FORECASTING PROGRAM ENROLLMENT

This section documents the analysis, modeling and assumptions that underlie the enrollment forecasts used to produce the residential program ex ante load impact estimates presented in Sections 5 through 7. The enrollment estimates underlying the non-residential SmartAC load impact estimates were produced by another contractor and are documented elsewhere.[36]

Forecasting customer enrollment in demand response programs is difficult in part because many programs are new and therefore there is little if any historical choice data that can be used to model and predict customer acceptance. For example, the PDP tariff has not yet been offered to customers and, therefore, no actual choice data exist that can be used to model future customer enrollment. Even when a program has been in place for several years, utilities typically market a program using a single approach and rarely collect information on the characteristics of customers who do and don't participate, thus making it difficult to model the relationship between customer acceptance, offer features and customer characteristics. Even when multiple marketing and promotional strategies are used, it is equally rare that a utility will implement these new approaches in a systematic, controlled way that would clearly support development of causal models linking a change in program features or marketing strategies to a change in enrollment. In short, it is unusual that actual choice data exist that allow for sound analysis of the relationship between customer acceptance of demand response options, promotional strategies and customer characteristics.

In the absence of such data, it is common to base choice analysis on survey information. Such surveys, often referred to as "stated preference surveys," ask consumers to indicate whether they would sign up for a program, or what choice they would make among several options. These survey responses can be used as dependent variables in choice models, with the explanatory variables representing customer characteristics and/or offer characteristics. While such surveys can be quite useful in understanding the relative preferences of consumers among several options, it is well known that many more customers will say they would accept such an offer than actually do. There are many reasons for this upward bias, including the fact that transaction costs reduce customer acceptance in the real world but are not factored into stated preference survey responses, and the fact that customers often say yes to an offer in a survey because they think that is what the surveyor wants them to say.

The enrollment forecasts used to produce PG&E's residential ex ante load impact estimates are based on a combination of modeling using actual choice data, insights gained from a stated preference survey, program goals and logical assumptions. As discussed in subsequent sections, in 2009, PG&E tested a variety of different marketing strategies for SmartRate that allowed us to estimate models that predict the likely acceptance rate for SmartRate as a function of various factors such as sign up incentives, promotional messages and contact frequency (e.g., whether a customer was sent more than one promotional piece). Data on offer characteristics and customer decisions were combined with data on customer characteristics from PG&E's customer

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[36] Joe Wharton, Ph.D., Armando Levy, Ph.D., Doug Mitarotonda, Ph.D., Sean Ogden, and Jenny Palmer (The Brattle Group, LLC) and Bruce Perlstein, Ph.D. (Strategy, Finance & Economics, LLC), *The 2010 – 2020 Enrollment Forecasts for PG&E's Demand Response Programs for Non-Residential Customers* (April 1, 2010)

information databases and US Census data so that the choice models reflect not only the impact of variation in promotional strategies but also variation in customer characteristics.

As indicated in Section 2, the CPUC has directed PG&E to abandon SmartRate at the end of 2010 and to offer instead a new Peak Day Pricing tariff. The adopted PDP tariff is quite similar to SmartRate in terms of the magnitude of the peak-period price on event days and the fact that the price differential on normal weekdays is quite small. As such, the choice models developed for SmartRate are likely to be very accurate for predicting future enrollment in PDP. At the time this work began, there was significant uncertainty about whether the CPUC would approve the PDP tariff it did or a different tariff, called Alternative 2 (or PDP2 here), that had a much higher peak period price on PDP days and greater rate differentials and peak period prices on other weekdays compared with the adopted tariff. Given that PDP2 was sufficiently different from the adopted tariff, there was less confidence that a model based on SmartRate choice data would be suitable for estimating future enrollment in PDP2. As such, PG&E commissioned a stated preference survey of customers' willingness to enroll in both PDP tariffs. The survey also asked about customer interest in a static TOU rate similar to PG&E's E6 tariff. Modeling and analysis using the stated preference survey data indicated that there is little difference in customer's acceptance rates between SmartRate, PDP1 and PDP2. Given this, the choice models based on SmartRate actual choice data are used to predict future enrollment in PDP, since analysis based on actual choice data is much more accurate than using stated preference data even when the models are used to predict for choices that are slightly different than those upon which they are based.

Future enrollment in PG&E's TOU tariffs, E6 and E7, were determined based on the following set of assumptions. As discussed in Section 2 of Volume 1 of this evaluation, more than 12,000 out of the 78,000 current E7 customers are net metered and almost 6,000 out of 7,400 E6 customers are net metered. Net metered customers are highly likely to have solar installations and, thus, have a very different pattern of energy use than a standard metered E6 or E7 customer. Data do not exist for a suitable control group for E6 or E7 net metered customers, so impacts for this group could not be developed. As such, the enrollment forecasts and impact estimates presented here cover only standard metered E6 and E7 customers.

The E7 tariff has been closed for several years, so future enrollment can be modeled based on the current enrollment level for standard metered customers (65,409) minus expected attrition in each future year. The E6 tariff is open to future enrollment. However, at this time, PG&E has no plans to actively market this tariff, choosing instead to focus all of its marketing effort on dynamic tariffs such as PDP and, depending on future regulatory decisions, Peak Time Rebates.[37] Given the small number of current, standard metered E6 customers (1,414) and the significant uncertainty concerning future enrollment, we have folded the E6 customers into the E7 tariff category and treated them as if they are the same for both enrollment and impact estimation.

Residential SmartAC enrollment estimates through the end of 2011 (the current program funding cycle) are the same as those provided in PG&E's SmartAC update filing.[38] As indicated in that filing, PG&E plans to have approximately 206,000 residential customers enrolled in the program by the end of 2011, with higher enrollment in hotter climate regions. The number of air

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[37] A.10-02-028 2010 Rate Design Window, Peak Time Rebate for Approval of funding request for years 2010-2013

[38] A.09-08-018, *Application of Pacific Gas and Electric Company (U 39 E) for Approval of 2010-2011 SmartACTM Program and Budget: Pacific Gas and Electric Company Prepared Testimony.*

conditioning units controlled (control devices installed) for this group of customers is expected to equal 227,000, with approximately 80% of the devices on these units being load control switches and the remaining 20% being PCTs.

As previously mentioned, enrollment estimates for non-residential customers were developed by another contractor, The Brattle Group (TBG). Enrollment is expected to increase from the current level of around 1,000 customers to 6,900 customers by the end of 2012 and then stay at that level for the remainder of the forecast period.

The remainder of this section documents the analysis that was done in support of the enrollment projections that underlie the ex ante load impact estimates presented in subsequent sections. Section 4.1 focuses on SmartRate/PDP enrollment. Section 4.2 briefly presents the TOU enrollment estimates for each year, and explains the attrition analysis that underlies these estimates. Section 4.3 presents the enrollment estimates by LCA for residential SmartAC participants.

4.1. SMARTRATE ENROLLMENT

This section begins with a summary of the promotional strategies that were used by PG&E over the last two years to market SmartRate. Summary statistics are provided showing how enrollment rates vary across promotional campaigns. However, these summary statistics can be misleading as a variety of factors (both promotional features and population characteristics) vary across campaigns. Parametric modeling is used to sort out the independent effects of these factors. This analysis is summarized and a number of “out of sample” validation tests are done to show that the model accurately predicts customer acceptance. A brief summary of some analysis that was done using the stated preference survey for PDP is also provided, although these data were not incorporated into the enrollment forecasting model for reasons summarized above. The final subsection summarizes the enrollment forecasts that are used in Section 5 to estimate average and aggregate load impacts for PDP from 2011 through 2020. SmartRate estimates for 2010 were obtained from PG&E’s marketing group based on a recently developed strategy to target high value customers, with a goal of obtaining approximately 35,000 new program participants by the end of 2010.

4.1.1. SmartRate Enrollment in 2008 and 2009

PG&E began recruiting into the SmartRate program in May 2008 in the Kern County region where SmartMeters had been installed prior to that time. All of PG&Es marketing campaigns for SmartRate have involved direct mail promotion. In the initial campaign in Kern County, PG&E used a business letter format on the company’s letterhead. The cover letter and enclosed brochure promoted the SmartRate as a way to save on one’s electricity bill and offered a $50 incentive for enrolling. Participating customers were also provided with bill protection for the first year they would be on the tariff. The bill protection provision offered customers a guaranteed refund of the difference between their bill under the SmartRate tariff and their bill based on the standard E1 tariff. The overall response rate to the 2008 marketing effort was 8.5%.

In 2009, PG&E modified its strategy for recruiting SmartRate participants. It varied the message and the format of its letters and offered incentives in only a fraction of its campaigns. PG&E also experimented with targeting its offer to certain customer segments based on enrollment in PG&E’s SmartAC program and, separately, on household psychometric profiles. The “psychometric” targeting experimented with different messages aimed at different customer segments, appealing to the environment or family values in the letter. In many cases, PG&E sent follow-up letters to customers who had not responded to the first offer. Some of those follow-ups changed the letter format and added an incentive to the offer.

Table 4-1 presents a summary of the offer formats, messages, and target customer segments. In all, PG&E sent out over 750,000 letters to 561,000 customers in 2009. Those letters were mailed at different times of the year in separate mailing campaigns, referred to as waves. PG&E sent out one or more follow-up letters, referred to as touches, to over 150,000 customers.

Table 4-1
Summary of 2009 Marketing Campaigns for SmartRate

Marketing Attribute	Description
Wave	7 initial mailings to different customer groups, at different times between February and September 2009
Touches	Follow-up mailings (2) to subsets of customers in waves 1 and 2
Format	#10 letter with business reply envelope
	Folded brochure with tear-off reply postcard
Message	"using less energy isn't the only way to shrink your bill"
	"shrink your bill and save more for your family"
	"a smaller impact on the planet. A smaller bill for you."
Incentive	None
	\$25 (Wave 0)
	\$50 (Wave 1, 3rd touch, Wave 2, 3rd touch, Wave 6)
Target Segment	No Targeting
	SmartAC Participants (Wave 0 and Wave 1 subset)
	Psychometric Personas (Waves 3, 4, and 5)

Table 4-2 summarizes the acceptance rates for the 2009 mail campaign waves and touches. The table shows the number of letters sent out in each wave as well as the number and percentages of responses to each offer. Response is summarized in two ways. The first is the number of acceptances divided by the number of mail pieces sent and the second is the number of acceptances divided by the number of customers contacted. If a campaign only involved a single mailing, the two values are the same. Waves 1 and 2 involved multiple mailings and, therefore, the enrollment rate at the end of the process was higher than the acceptance rate for any single mailing. In total, the average response rate to each mailing was 2.5% and the overall enrollment rate was 3.3% of customers contacted one or more times.

The offers to customers already enrolled in the SmartAC program had the highest success rate by far. The first offer to SmartAC customers, sent out in February (Wave 0) along with a \$25 incentive, achieved a 24% enrollment rate. A later mailing to SmartAC customers in July, sent out as part of Wave 1 without the incentive, achieved an enrollment rate of 15%.

Aside from those waves, the next most successful single mailing was the last one (Wave 6), mailed in September - which included a \$50 rebate. 3.6% of the recipients of that mailing accepted the offer. When PG&E sent follow-up offers to customers who had not responded to earlier ones (with the second follow-up offering a \$50 incentive), a cumulative response rate of 7.4% (Wave 1) and 4.1% (Wave 2) was achieved across the multiple touches.

Table 4-2
SmartRate Enrollment from 2009 Marketing Campaigns

Wave	Total Mailings	Total Customers	Customers Enrolled	Acceptance Rate (%)	Enrollment Rate (%)
0	3,862	3,862	921	23.9%	23.9%
1	104,422	59,010	4,348	4.2%	7.4%
2	272,994	127,938	5,258	1.9%	4.1%
3	169,455	169,455	3,989	2.4%	2.4%
4	39,115	39,115	810	2.1%	2.1%
5	121,709	121,709	1,886	1.6%	1.6%
6	39,720	39,720	1,428	3.6%	3.6%
Total	**751,277**	**560,809**	**18,640**	**2.5%**	**3.3%**

The other offerings in 2009, with various messages and letter formats, achieved response rates ranging from 1.9% to 2.9%. Table 4-3 summarizes the variation in response rates with respect to letter format and marketing message. Those response rates do not show any strong pattern with respect to message and letter format, at least based on the simple tabulations. After excluding mailings directed at SmartAC participants and those offering incentives and the follow-up mailings, some modest differences, presented in Table 4-3, become evident. The self-mailer format produced a response rate of 2.8%, versus a response rate of 2.5% for the letter format. The "bill reduction" marketing message achieved a 2.9% response rate, versus a 2% response rate to messages that emphasized the environment or family values.

It is important to emphasize, however, that these simple comparisons may not accurately reflect the true effects of alternative promotional strategies on response rates because they are combined with other factors that determine response rates. Identifying the individual effects of each promotional feature is treated through a parametric analysis of the response rates, the results of which are presented and discussed below.

Table 4-3
Acceptance Rates for Selected Promotional Approaches

Promotional Characteristics	Total Customers Contacted	Customers Enrolled	Acceptance Rate (%)
Mail Format--#10 Letter	229,896	5,866	2.5%
Mail Format—Self Mail Brochure	400,768	11,482	2.8%
Tiny Bill Message	470,426	14,081	2.9%
Environmental Message	83,237	1,741	2.1%
Family Oriented Message	77,001	1,526	1.9%

In addition to a significant increase in response rates when offers were targeted at SmartAC participants and when an incentive was offered, response rates varied based on differences in customer characteristics. Information on customer characteristics was available from PG&E's general residential database and by appending CBG data to customer records, as discussed in Section 3. Table 4-4 shows the average values of characteristics between customers who enrolled (participants) and those who declined to enroll (non-participants), including electricity usage patterns, customer participation in other PG&E programs or past use of other PG&E services, weather and neighborhood characteristics based on CBG data.

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Table 4-4
Selected Household Characteristics of SmartRate Participants and Non-Participants

Variable	Non-Participant Mean	Participant Mean	Difference
Average Annual Electricity Consumption (kWh)	7812	7491	321*
Summer Electricity Consumption (kWh)	799	791	8
Percent Enrolled in SmartAC	2.4%	11.2%	8.8%*
Percent enrolled in CARE	30.4%	46.5%	16.1%*
Annual Cooling Degree Days (2007-08)	1482	1648	167*
Median Age (head of household)	47.2	47.1	0.1
Median Home Value (1000s)	408	387	21*
Average household size	3.5	3.56	0.06
Median Year house was built	1977	1976	1
Median household income	62033	60260	1773*
Percent owner-occupied Homes	63.1%	63.6%	0.5%
Percent Spanish speaking households	19.2%	22.1%	0.3%*
* Difference is significant at the 95% confidence level			

4.1.2. Parametric Analysis

The individual effects of the different promotional characteristics on enrollment in the SmartRate Program, after controlling for other characteristics, are best examined through parametric statistical analysis. In that framework, all of the alternative marketing strategies – letter format, message, and targeting – are considered together in a multivariate statistical regression. In this case, the analysis differs from the standard regression model because the dependent variable – an indicator of whether the customer accepts the offer – can only take on two values, corresponding to “yes” or “no”. The analysis uses a binary probit regression model that is well suited for this application. That specification models the probability of acceptance as a function of marketing attributes and customer characteristics. The functional form for the probit ensures that the probability ranges between zero and one. The model specification is as follows:

$$\Pr\left(Enroll_j\right) = \Phi(\mathrm{U_j})$$

$$\begin{aligned}U_j = {} & \beta_0 + \beta_1 linincent + \beta_2 SAC + \beta_3 CARE + \beta_4 \ln incentxSAC + \beta_5 \ln incentxCARE \\ & + \beta_6 \ln incentxSACxCARE + \beta_7 \ln incentxM\_income + \beta_8 SACxCARE \\ & + \beta_9 * \Pr e - summer + \beta_{10} * Early\_summer + \beta_{11} * Late\_summer \\ & + \beta_{12} * pct\_spanish_j + \beta_{13} * Sofferxpct\_spanish_j + \beta_{14} * Sofferxpct\_spanishxCARE \\ & + \beta_{15} * CS\_letter +_{16} \beta_{16} * CS\_Brochure + \beta_{17} * E\_Brochure + \beta_{18} * F\_Brochure \\ & + \sum_{19}^{21} \beta_i * Touch_i + \beta_{22} * CAC\_propensity + \beta_{23} * CDD65 + \beta_{24} * CACxCDD65 \\ & + \beta_{25} * M\_income + \beta_{26} \ * Pct\_own + \beta_{27} * Urban + \beta_{28} * EE \operatorname{Re} bate09 \\ & + \beta_{29} * EE \operatorname{Re} bate03 - 08 + \beta_{30} * Avg\_hhsize + \sum_{31}^{34} \beta_i * \operatorname{Re} gion_i \\ & + \beta_{35} * Avg\_kwh + \sum_{36}^{39} \beta_i * Avg\_kwh * \operatorname{Re} gion_i + \beta_{40} * M\_hvalue \\ & + \beta_{41} * Pct\_lt18 + \beta_{42} * Pct\_wochild + \sum_{1949}^{2009} \beta_i * V_i\end{aligned}$$

Variable	Definition
Choice (Y/N)	Binary indicator, equal to 1 if the customer responded to the most recent SmartRate offer, 0 otherwise (dependent variable in enrollment model)
Lnincent	The natural log of the level of incentive offered in SmartRate mailing (0, 25, and 50 in sample), plus 1
SAC	Binary indicator, equal to 1 if the customer is enrolled in SmartAC, 0 otherwise
CARE	Binary indicator, equal to 1 if the customer is enrolled in CARE, 0 otherwise
lnincentxSAC	lnincent times binary indicator of whether customer is enrolled in SmartAC
lnincentxCARE	lnincent times binary indicator of whether customer is enrolled in CARE
lnincentxSACxCARE	lnincent times SAC times CARE
Lnincentxmincome	lnincent times median household income for neighborhood (Census Tract)
SACxCARE	SmartAC times CARE
Season (mail date)	
pre-summer	Binary indicator, equal to 1 if offer was mailed before June, 0 otherwise
early_summer	Binary indicator, equal to 1 if offer was mailed in June or July, 0 otherwise
late_summer	Binary indicator, equal to 1 if offer was mailed in July or August, 0 otherwise
pct_spanish	Percent of households in neighborhood (Census block group) who speak Spanish
Sofferxpct_spanish	Binary indicator of whether mailing was multilingual campaign (English/Spanish) times percent of households in neighborhood who speak Spanish
Sofferxpct_spanishx CARE	Binary indicator of whether mailing was multilingual campaign (English/Spanish) times percent of households in neighborhood who speak Spanish times CARE
DM Marketing Piece	
CS_letter	Binary indicator, equal to 1 if offer was sent in a #10 letter and featured a "cost savings" theme
CS_Brochure	Binary indicator, equal to 1 if offer was sent in a folded brochure and featured a "cost savings" theme
E_Brochure	Binary indicator, equal to 1 if offer was sent in a folded brochure and featured a "help the environment" theme
F_Brochure	Binary indicator, equal to 1 if offer was sent in a folded brochure and featured a "save more for your family" theme
Touch	
Touch1	Binary indicator of whether the mailing was the first one (touch)
Touch2	Binary indicator of whether the mailing was the second one (touch)

Variable	Definition
Touch3	Binary indicator of whether the mailing was the third one (touch)
	Customer Characteristics
CAC_propensity	Indicator of the likelihood that a household has a central air conditioner
CDD65	Annual cooling degree days to base of 65 degrees in 2007-2008 (in thousands)
CACxCDD65	Central Air Conditioner Likelihood indicator times Annual CDD
M_income	Median Household income for neighborhood
Pct_own	Percent of owner-occupied homes in neighborhood (Census block group)
Urban	Percentile of urban density (population per square mile) for the neighborhood (Census Block group)
EErebate09	Indicator of whether customer received an energy efficiency rebate in 2009
EErebate03-08	Indicator of whether customer received an energy efficiency rebate in 2003-2008
Avg_hhsize	Average number of persons per household in neighborhood (Census block group)
	Climate Region
Region_R	Indicator of whether customer is located in Climate Region R (Fresno, Bakersfield)
Region_S	Indicator of whether customer is located in Climate Region S (Stockton, Sacramento)
Region_T	Indicator of whether customer is located in Climate Region T (Coastal, Peninsula)
Region_X	Indicator of whether customer is located in Climate Region X (East Bay)
Avg_kwh	Average monthly electricity consumption for 10/08-09/09
Avg monthly kWh x CARE	Avg Monthly kWh times CARE
	Average kWh x Region
Avg_kwhxRegion_R	Avg Monthly kWh times Region R
Avg_kwhxRegion_S	Avg Monthly kWh times Region S
Avg_kwhxRegion_T	Avg Monthly kWh times Region T
Avg_kwhxRegion_X	Avg Monthly kWh times Region X
M_hvalue	Median value of homes in neighborhood (Census Block group)
Pct_lt18	Percent of households with children (members under 18)
Pct_wo_child	Percent of households without children
	Neighborhood Home vintage (CBG)
Vlt1949	Binary indicator, equal to 1 if median age of home in neighborhood earlier than 1949, 0 otherwise
V1950-59	Binary indicator, equal to 1 if median age of home in neighborhood is 1950-1959, 0 otherwise
V1960-69	Binary indicator, equal to 1 if median age of home in neighborhood is 1960-1969, 0 otherwise
V1970-79	Binary indicator, equal to 1 if median age of home in neighborhood is 1970-1979, 0 otherwise
V1980_89	Binary indicator, equal to 1 if median age of home in neighborhood is 1980-1989, 0 otherwise
V1990-99	Binary indicator, equal to 1 if median age of home in neighborhood is 1990-1999, 0 otherwise
V2000-09	Binary indicator, equal to 1 if median age of home in neighborhood is 2000-2009, 0 otherwise

The estimated coefficients are shown in Appendix B. The dependent variable in the model is an indicator (yes/no) of whether the customer accepted the most recent offer. The explanatory variables represent the various marketing attributes of the different waves and interactions among them, as well as the demographic, locational, electricity consumption and past customer participation in other PG&E programs.

Overall, the model results and estimated coefficients appear reasonable and most are statistically significant in explaining variation in enrollment rates. Certain promotional strategies produce significantly higher response rates than others, and certain demographic groups are significantly more likely to enroll than are others.

As expected, the incentive was very effective in stimulating the acceptance rate, after controlling for other marketing attributes. In the model reported in Appendix B, the explanatory variable representing the incentive enters as the natural log of the amount (lnincent),[39] capturing the expectation that an increase from $0 to $25 would have a greater effect than an increase from $25 to $50. The estimated model coefficient supports that expectation.

The incentive variable also enters the model interacting with binary indicators of whether the customer was on CARE (lnincent#CARE), whether they were enrolled in SmartAC (lnicent#SAC), and whether they were enrolled in both (lnincent#CARE#SAC). Even without the incentive, SmartAC and CARE customers are much more likely to enroll in SmartRate than other households. But for attracting CARE customers (who are not already enrolled in SmartAC), the incentives are even more effective than for non-CARE customers. The same is not true for SmartAC participants, however. Although SmartAC participants are much more likely to enroll in SmartRate than other customers, the incentives do not provide any additional effect in attracting them beyond the effect of incentives for other non-CARE customers

The coefficient estimates for the letter format and marketing messages are plausible and statistically significant. The #10 letter format with a cost savings theme achieves a higher response rate than the folded brochure.

Likewise, the folded brochure format with the environmental and family messages is more effective than the brochure with the simple cost-saving message. Both of the findings for the letter format and the promotional message based on the probit model contrast with the results from the simple cross-tabulations, where the response rates were higher for the mailings that used a brochure format and a simple cost-savings message.

The mailings that were sent out earlier in the year were more effective than the later mailings, after controlling for other factors. Mailings sent out before June would be expected to achieve almost a 2.5% higher response rate than those sent out in August and September, based on the model. Put another way, customers appear more willing to participate in time-based pricing when it is offered before the heart of the summer period. Once the weather turns hot and they are reminded of the value of air conditioning, they are less likely to sign up.

As expected, in cases where customers received follow-up mailings (touches), response rates were lower for second and third contacts than for the first. In the absence of an incentive, the response rate declined from 2.5% in the first mailing to 1.6% in the third. However, cumulative response rates increase with multiple mailings. Likewise, multilingual mailings were more effective in neighborhoods with higher percentages of Spanish-speaking households.

Due to the non-linear nature of the model, the magnitudes of the effects of alternative marketing strategies depend on the levels of the other characteristics. For example, a $50 incentive increases response rates by 3.3 percentage points, from 2.5% to 5.8% in the first touch (mailing to a given customer). But a $50 incentive increases the response rate by only 2.3 percentage points in the third touch (from 1.7% to 4.0%).

[39] The actual algebraic transformation of incentive is the natural log of (the level+1), so that the variable is defined for an incentive level of zero.

At the mean values for all other variables in the model, when no incentive is offered, the estimated average response rate is 2.4%. An incentive offer of $25 would increase the response rate to 4.9%, and a $50 incentive would produce a 5.6% positive response. Thus, the additional effect of increasing the incentive diminishes as the incentive value increases.[40]

Without an incentive, the letter format with the bill saving message increased acceptance rates by 0.7% over the brochure format with the same message (2%), to an average of 2.7%. The brochure with the message appealing to the environment ("a smaller impact on the planet, a smaller bill for you.") was the next most effective (after the letter format) in stimulating response rates (2.4%). The brochure with the message appealing to family ("shrink your bill and save more for your family") was only slightly less effective (2.3%).

The results of this analysis also indicate that past enrollment patterns are strongly related to several demographic attributes, locational variables and information in PG&E's billing system. Significant explanatory variables include CBG attributes such as home value, household income, number of children per household (i.e. persons less than 18 years of age), percent of households without children, percent Spanish speaking households (for multilingual campaigns), and the age of the home. All of those variables represent the mean or median value for the CBG. Locational variables include climate region and average cooling degree days per year. Information drawn from PG&E's internal customer information system includes annual and seasonal electricity consumption, CARE participation, and whether the customer had received a PG&E rebate in the past.

Recipients of other PG&E energy efficiency services (EERebate) are more likely to enroll than the average customer. Recipients of rebates between 2003 and 2008 were about 0.5% more likely to sign up for SmartRate (3.6% versus 3.1%), and recipients in 2009 were 1.7% more likely (4.9% versus 3.2%).

Both of the locational variables – indicators of the climate region and the annual cooling degree days (based on weather station) – are statistically significant in the model. The most important climate regions, both statistically and numerically, are the indicators for Stockton/Sacramento and East Bay. The predicted enrollment rates for the Stockton/Sacramento and East Bay customers are 6.2% and 3.7%, respectively, relative to the average of 3.3% for the entire sample. This estimate controls for cooling degree days, which also has a strong impact on enrollment, as well as for other important variables. The enrollment rates are significantly higher in hotter areas. They are almost 80% higher in areas with 2,800 cooling degree days (6.1%) versus areas with 1,800 CDDs (the system wide average).

Statistically, the most significant census variables that explain SmartRate enrollment patterns are median owner-occupied home value, median current household income, percent of homes that are owner occupied, average household size, and indicators of the median age of the homes. But the numerical differences in enrollment rates with respect to differences in home values are moderate. A change in the median value of a home from the sample average of $410,000 to $510,000 increases enrollment rate by less than 0.2%. Similarly, an increase in the median

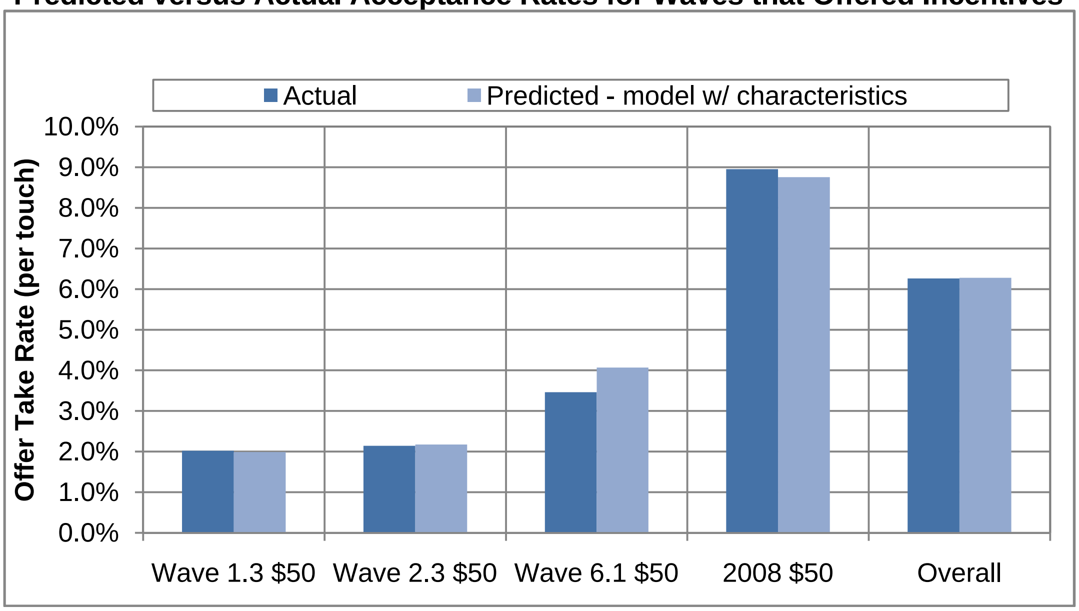
[40] This result holds true for a more general model, not reported here, where the effects of the incentive level is not constrained to a log form. That general model does not improve the overall explanatory power of the results, and it produces enrollment predictions that are virtually the same as the ones based on the model presented here.

annual household income by $10,000 is associated with an average increase in enrollment of 0.2% from the sample average of $62,000. Married couple households are slightly more likely to enroll than non-married households. The effect is weak, however, and the numerical effects on enrollment rates are small.

Customers' annual and seasonal electricity consumption are significantly related to SmartRate enrollment. Once again, however, the predicted effects on enrollment rates are small. An increase in average monthly electricity use by 10% results in less than a 0.1% increase in enrollment rates.

The performance of the model summarized above was assessed by comparing the predicted and actual acceptance rates for the SmartRate offer based on differences along several dimensions. First, the predicted and actual rates were compared by wave and touch.[41] Those are broken down between the waves that offered incentives (Figure 4-1) and those that did not (Figure 4-2).

Figure 4-1
Predicted versus Actual Acceptance Rates for Waves that Offered Incentives



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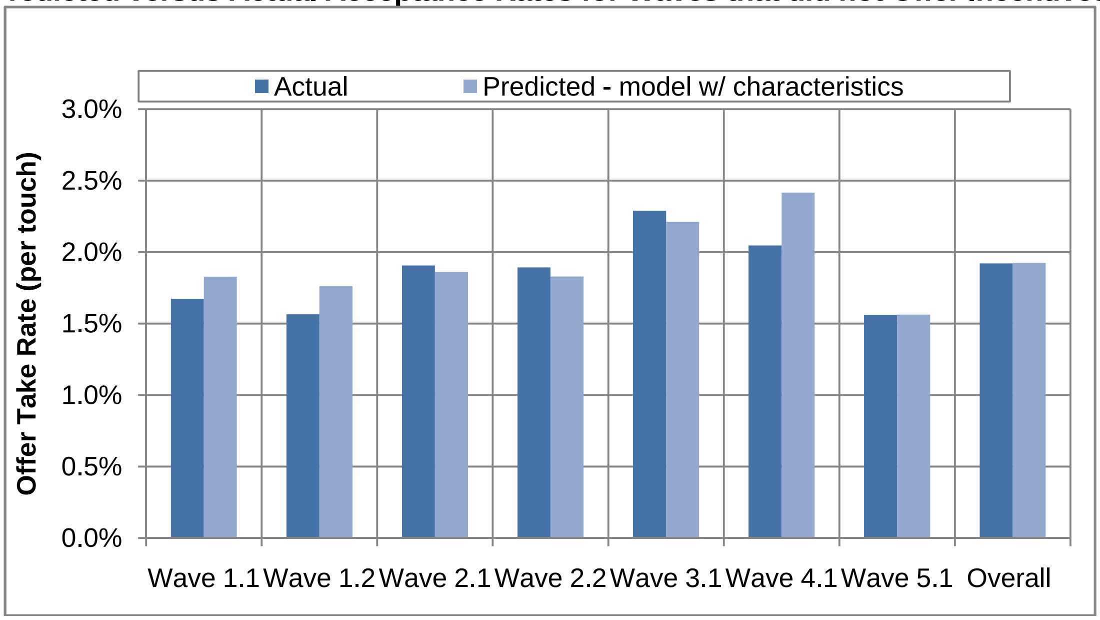
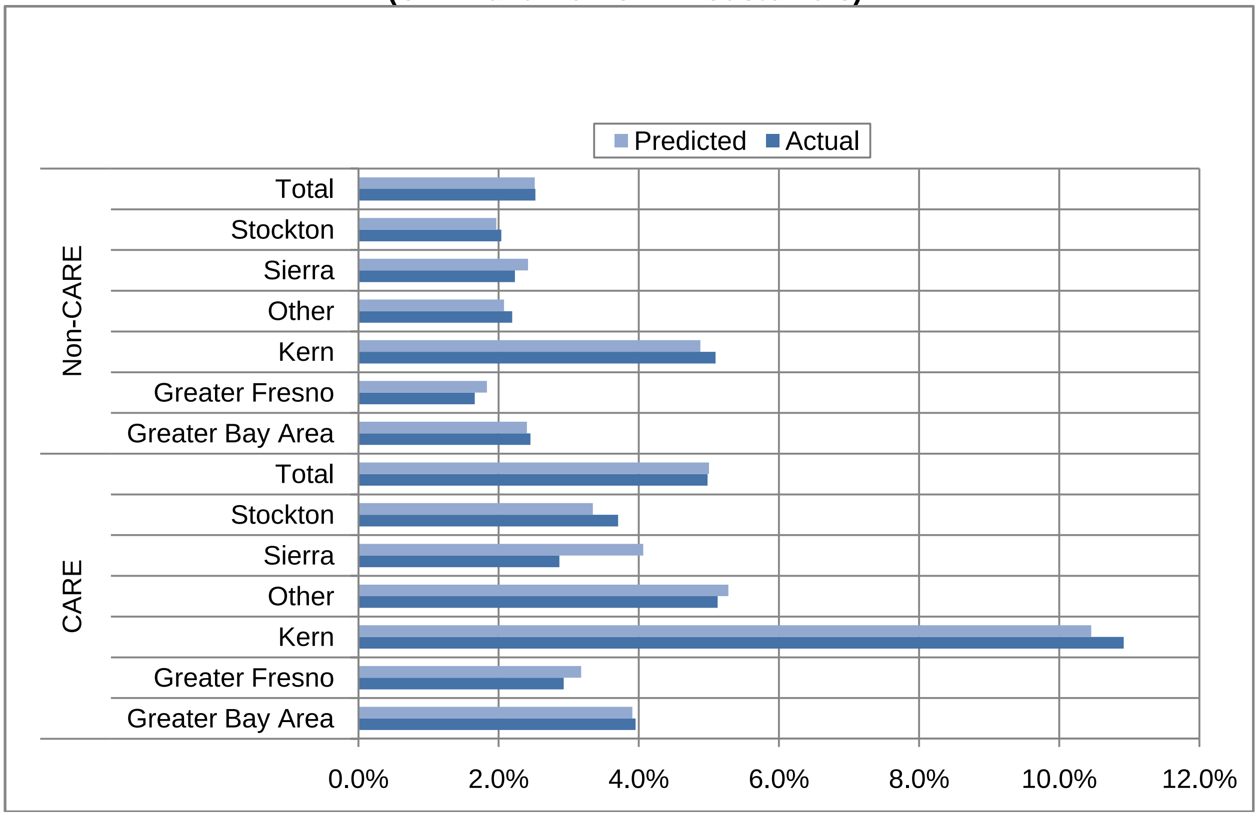
[41]In the tables, the wave/touch combinations are denoted as wave #.touch#. For example 1.2 represents wave 1 and touch 2.

Figure 4-2
Predicted versus Actual Acceptance Rates for Waves that did not Offer Incentives



Next, we examined the acceptance rates by local capacity area and whether the customer is enrolled in the CARE program (Figure 4-3). Once again, the model predicted quite well, especially for all of the most populous LCAs

Figure 4-3
Predicted and Actual Acceptance Rates by Local Capacity Area
(CARE and Non-CARE Customers)



4.1.3. Customer Acceptance of Peak Day Pricing Tariff

In order to investigate customer acceptance of the proposed PDP tariffs, PG&E commissioned a survey asking respondents whether they would sign up for a new tariff if offered in the future. The survey described the alternative tariff (referred to as an Off-Peak Savings Plan in the survey), promoted as a way to control costs and lower greenhouse gases. Bill protection was also part of the offer description. These offer characteristics are similar to what PG&E has included in its SmartRate mailings.

The survey was mailed to a representative, stratified sample of PG&E residential customers, and almost 61% of the households replied. Recognizing that survey respondents may be more favorably inclined toward the PDP tariffs, the summary statistics reported below treat a non-response as an implicit “no” to the key question about whether they would sign up for the PDP tariff.

The survey was stratified by twelve different segments. Those segments corresponded to whether a customer was enrolled in 1) CARE (yes/no), 2) the SmartAC Program, SmartRate Program, or neither, and 3) whether the respondent was asked about the PDP1 or the PDP2 tariff, making 2X3X2= 12 segments. In addition, a survey about SmartRate was administered to a “calibration” sample of CARE and non-CARE households. That calibration sample was designed to allow direct comparisons between the survey-based acceptances of the voluntary tariffs and “real world” acceptance rates of the SmartRate tariff.

The responses to the question, “would you choose the off-peak savings plan or the standard service plan?” are summarized in Table 4-5. The overall (unweighted) acceptance rate of the PDP tariffs among respondents who answered (i.e. excluding those who responded “not sure”) was over 40%. There was only a 1% difference in the acceptance rates between the PDP1 (41%) and the PDP2 (40%) tariffs in the survey. Among CARE customers, the positive response was moderately lower (35%) than for the non-CARE population as a whole (42.5%).

Among customers already enrolled on the SmartRate Program, almost 53% said they would prefer the PDP tariff (i.e. off-peak savings plan) over the flat rate (standard service plan). There was only a slight difference in preferences between the two PDP tariffs, with over 52% selecting PDP2 versus 53.5% for PDP1. The preference for the PDP tariffs was weaker among CARE customers on SmartRate (52%) than among non-CARE customers (42%). CARE customers on SmartRate showed a small preference for PDP1 (42%) over PDP2 (41%).

The preferences of customers on SmartAC, PG&E’s air conditioner cycling program, toward the PDP tariffs were not as strong as those of SmartRate customers. 45% said they would select PDP over the flat rate. There was little overall difference in preferences between PDP1 and PDP2 for non-CARE customers, but CARE customers were much less favorable toward PDP overall (39% for CARE customers versus 47% for non-CARE customers) and less inclined toward PDP2 (34.7%) than toward PDP1 (42.3%)

22% of the customers who were not already enrolled in either the SmartAC or the SmartRate programs (referred to as Greenfield customers) said they would prefer the PDP tariff over the flat rate. “Greenfield” non-CARE customers showed virtually no difference in preferences for PDP1 versus PDP2 tariffs. But “Greenfield” CARE customers showed moderate preference for the PDP1 tariff (22%) over PDP2 (18%).

Table 4-5
Percent of Customers Indicating Willingness to Accept Tariff Offer in Stated Preference Survey

Segment	Yes	No	Total	Acceptance Rate (%)
Greenfield PDP1 CARE	42	148	190	22.11%
Greenfield PDP2 CARE	38	176	214	17.76%
SmartAC PDP1 CARE	88	120	208	42.31%
SmartAC PDP2 CARE	67	128	195	34.36%
SmartRate PDP1 CARE	137	180	317	43.22%
SmartRate PDP2 CARE	140	199	339	41.30%
Greenfield PDP1 Non-C	152	534	686	22.16%
Greenfield PDP2 Non-C	160	526	686	23.32%
SmartAC PDP1 Non-Care	360	408	768	46.88%
SmartAC PDP2 Non-CARE	365	412	777	46.98%
SmartRate PDP1 Non-CA	383	270	653	58.65%
SmartRate PDP2 Non-CA	366	273	639	57.28%
Total	**2,298**	**3,374**	**5,672**	**n/a**

Although the simple comparisons are useful in understanding acceptance rates, a parametric probit analysis allows one to identify any differences in preferences for PDP1 versus PDP2 after controlling for other factors such as whether a respondent is enrolled in the CARE, SmartAC, or SmartRate program.

Table 4-6 presents a simple model where these factors are included. In this case, the model results tend to confirm the findings of the simple cross tabulations. Customers already enrolled in SmartRate or SmartAC have a significantly stronger preference for the PDP tariffs, relative to “Greenfield” customers. There were no significant differences in the stated preferences for PDP1 versus PDP2 tariff for non-CARE customers. CARE customers have a weaker preference for the PDP rates overall than non-CARE customers, and they like PDP2 significantly less than PDP1. That result appears to stand up across all segments (Greenfield, CARE, SmartAC, and SmartRate participants) in additional model specifications that explore such possible interactions (not shown here).

Table 4-6
PDP Survey Stated Preference Choices

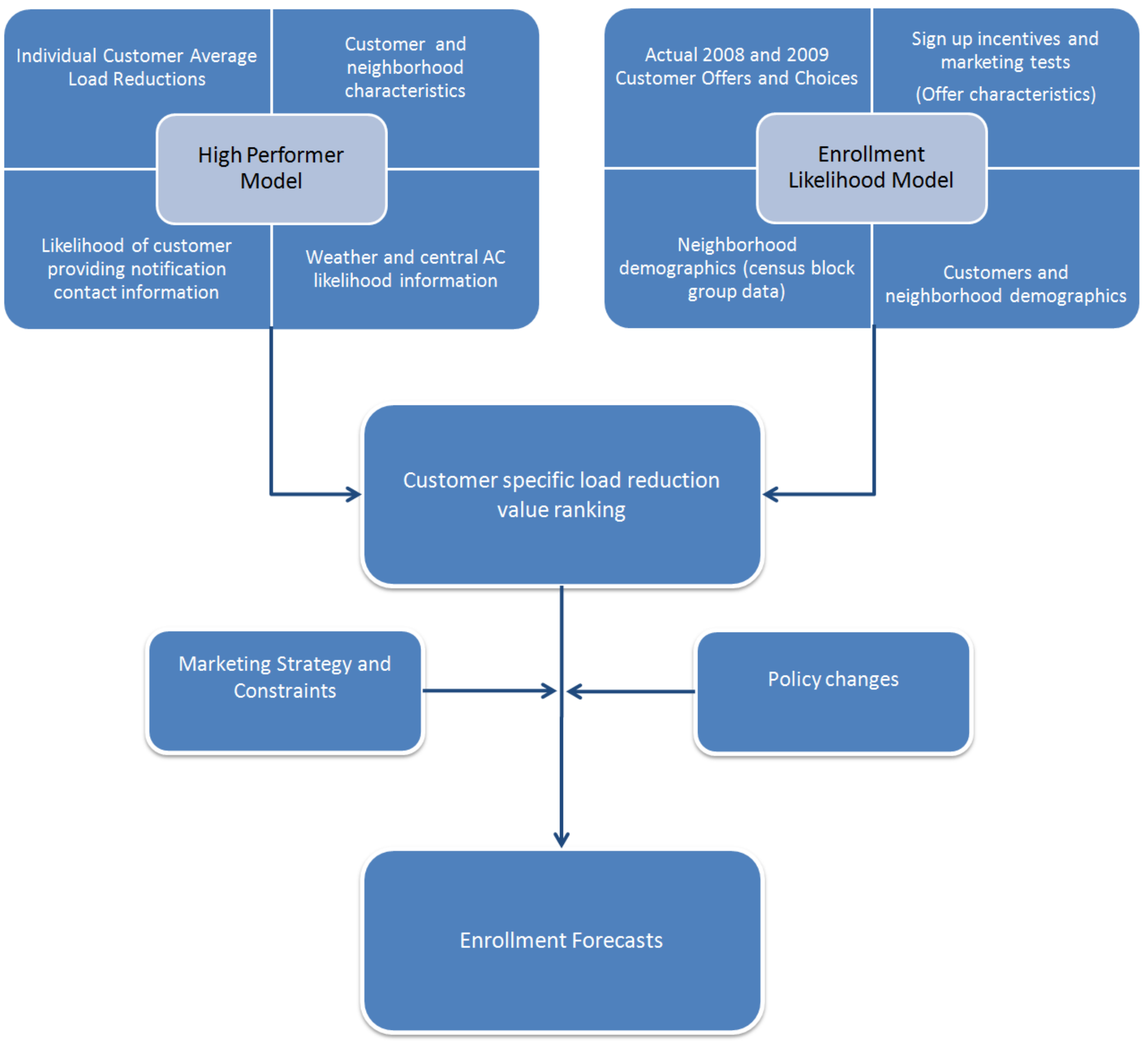
Variable	Coefficient	Std Error	z-statistic
PDP2	0.00	0.04	-0.01
SmartRate	0.87	0.04	19.71
SmartAC	0.64	0.04	14.72
care	-0.21	0.06	-3.65
PDP2xcare	-0.12	0.08	-1.50
Constant	-0.71	0.04	-17.96

The analysis summarized above indicates that acceptance rates are very similar between SmartRate, PDP1 and PDP2. These findings support the use of the SmartRate choice model summarized in Section 4.1.2 to predict customer acceptance rates for PDP1 for the years 2011 through 2020.

4.1.4. SmartRate/PDP Enrollment Projections

Estimates of enrollment in SmartRate in 2010 and in PDP in 2011 through 2020 were based on a variety of models and assumptions. A key assumption is that PG&E will identify and rank high performer, high likelihood customers and market to these high value customers in descending order over the forecast horizon. As part of this study, FSC applied SmartRate enrollment likelihood and load reduction performance models to all 4.5 million of PG&E's residential customers and provided the data to PG&E. Figure 4-4 summarizes the process used to identify the highest value customers.

Figure 4-4
Overview of SmartRate/PDP Enrollment Forecast Process



The model quantifying the extent to which customer characteristics, weather, central AC penetration, notifications, and various other factors affect price responsiveness was applied to the entire PG&E residential population. It was combined with individual customer estimates of the likelihood of enrollment under the most effective marketing approach. The information on high price responsiveness and high enrollment likelihood was used to produce a customer level value ranking to better optimize targeting. The enrollment simulations factored in our understanding of PG&E's marketing strategy for 2010. PG&E has not yet developed marketing plans for PDP starting in 2011. The targeting strategy underlying the enrollment forecasts presented here is conceptually consistent with PG&E's 2010 SmartRate marketing plan, although the specific models and tactics underlying the forecasts presented here and those currently being used by PG&E differ. PG&E will undoubtedly consider the key insights developed through the analysis presented in this report when developing its PDP strategy now that the final CPUC decision on PDP has been issued.

The enrollment estimates for each forecast year for SmartRate/PDP are based on the following factors and assumptions:

- Cumulative enrollment in each year equals the prior year's cumulative enrollment, minus attrition, plus new acquisitions. For SmartRate/PDP, attrition is based on the historical customer turnover rates for 2008 and 2009. The vast share of turnover in the program was due to changes in accounts associated with moves or account closings, which waere unusually high in 2009. A hypothesis for the high turnover is that the housing crisis and downturn in the economy affected account closings and relocations. A small number of program departures (818 out of approximately 30,000 customers) were explicit requests by customers to leave the SmartRate tariff after the bill protection period ended. Attrition rates were calculated by LCA by dividing the number of accounts closed by the number of exposure months. Across the service territory, customer turnover was approximately 15%, although turnover rates were generally higher in the Central Valley. For the enrollment modeling it was assumed that population turnover would return to more normal rates and a 12% annual turnover rate was applied.

- New enrollment in 2010 was based on predictions tied to marketing strategy that is conceptually similar to the one PG&E is currently implementing, which targets customers that are expected to provide high load reductions and have a high propensity to participate in SmartRate. The propensity estimates that PG&E is using in its targeting strategy for 2010 are based on internal, proprietary models. The estimates provided here are based on the choice models documented in Section 3. As such, there will be some difference between the estimates made here and the marketing and load goals that PG&E is pursuing in 2010.

- In 2011, when SmartRate ceases to be available, as directed by the CPUC, SmartRate customers will be defaulted onto PDP, and will be given an extra year of bill protection. Based on market research conducted by PG&E indicating that most SmartRate customers would stay on a rate structurally similar to PDP, and similarities between SmartRate and PDP in terms of peak-period prices, we assume that 90% of customers will stay through the end of the bill protection period.

- At the end of the bill protection period (early 2012), we assume that 70% of SmartRate customers that would have higher bills on PDP than on E1 (the otherwise applicable tariff) will leave. This higher attrition rate reflects the fact that high use customers have a greater likelihood of being a structural loser under the PDP tariff than under SmartRate. This reflects the fact that SmartRate was not designed to be a revenue neutral tariff for the average PG&E customer but, rather, was designed to be revenue neutral for the average customer in climate zones R and S. In other words, SmartRate was designed to attract customers with large loads that could provide large load reductions. PDP on the other hand was designed to be revenue neutral for the average customer across the entire service territory. As such, the high use customers defaulted onto PDP at the beginning of 2011 (many of whom reside in zones R and S) will be more likely to leave at the end of the bill protection period than would an average PG&E customer.

- SmartRate/PDP can only be offered to customers with SmartMeters. This limits the target population in 2010 and 2011.

- The promotional strategy in each year will offer customers a $50 sign up incentive. We also assume that the offer will be presented prior to the summer season, using a multi-lingual marketing campaign, with a plain letter envelope mail piece. This marketing approach incorporates the marketing factors that were found to be most effective in improving enrollment based on the actual choice data and tests conducted by PG&E as discussed in Section 3. Enrollments are typically higher with the initial offer (e.g., the first touch), with the response rate declining with subsequent offers.

- The promotional strategy will continue to use direct mail and will disperse roughly 600,000 mail drops each year, involving a combination of first, second and third "touches" for customers who do not accept the prior offers. This promotional pace is consistent with what PG&E is planning for 2010 and factors in PG&E's current strategy to balance marketing activity across various programs and to avoid contacting customers too often in any single year.

- In each year starting in 2011, customers who had not previously enrolled were ranked based on a combination of their likelihood of enrollment (based on the models discussed above), their expected load drop and estimates of their likelihood of providing contact information for event notification. Each year, it is assumed that PG&E actively targets the top load drop and enrollment prospects, although all customers are eligible to join the rate. After each round of marketing, the value ranking of customers was recalculated to incorporate the lower response rates associated with second and third offers. The likelihood of customers providing notification contact information was incorporated into the algorithm because, based on the 2009 ex post impact analysis, it was evident that customers who did not provide PG&E event notification information did not provide load response.

- After 2011, the enrollment modeling assumes that SmartAC is offered to customers who are believed to have air conditioning loads in excess of 1 kW, and load drops smaller than 20 percent. In other words, SmartAC would be offered when it is expected to provide incremental impacts. Note that the load impacts for customers enrolled in both SmartAC and PDP after 2011 have not been included in the estimates that are provided for long term planning, resource adequacy, or cost-effectiveness due to regulatory uncertainty. The scope of the SmartAC program after

2011 has not been determined and decisions from the ongoing, related proceedings for a Peak Time Rebate program can significantly alter the landscape and strategy.

- The enrollment modeling does not incorporate replacements for high value customers that leave the tariff due to turnover, introducing a degree of conservatism in the projections. In other words, high value customers are not restocked. In practice, customer turnover leads to enrollment losses but also new prospects.

Based on the enrollment assumptions summarized above, over the course of 11 years, PG&E would send 6,600,000 SmartRate/PDP direct mail offers and recruit almost 600,000 customers. While the take rate per offer is 9%, the optimization model assumed high value customers could receive second and/or third direct mail offers. Overall, 14.2% of customers offered the tariff are projected to enroll in SmartRate/PDP, with almost half enrolling based on a second or third offer. At the end of the forecast period, the cumulative enrollment is roughly half of the total who enroll over time due to the high assumed turnover (12%) and the anticipated participant losses in the transition from SmartRate to PDP.

The 9% enrollment rate per “touch” reflects a higher enrollment rate than was achieved in 2009, but is similar to enrollment rates achieved in 2008. The projected enrollment rates are higher than in 2009 for several reasons. First, the marketing strategy used here generally targets customers with a higher predisposition toward SmartRate/PDP – data that was unavailable for earlier marketing efforts.[42] Second, we assume that a $50 sign up incentive will be offered to customers. As discussed earlier in this section, the analysis of actual choice data conducted by FSC showed that sign up incentives significantly increase the likelihood that customers will enroll. Except for small test beds, most customers in 2009 were not offered sign-up incentives. Finally, the 2009 marketing tests produced empirical evidence regarding the effectiveness of marketing strategies that were unavailable for 2009 marketing, including the effect of incentives, dual marketing, timing, format, and repeated offers. All of these new insights have been incorporated into the enrollment estimates provided below.

Table 4-7 summarizes the expected number of participants over the forecast horizon by local capacity area, after factoring in annual attrition and turnover. Under the marketing strategy assumptions detailed above, the opt-in SmartRate\PDP tariff is predicted to cumulatively enroll almost 300,000 accounts, despite the significant customer turnover and the non-trivial projected loss of participants during the 2011-2012 rate transition. Noticeably, when both enrollment and load reduction performance are factored in, the distribution of participants is not solely concentrated in hotter parts of the PG&E territory.

As discussed above, the drop in enrollment in 2012 results from the transition from SmartRate to PDP and the anticipated exit of numerous high load customers who will likely find it more difficult to obtain bill savings under the revenue neutral PDP tariff. However, as seen in Table 4-7, enrollment is predicted to bounce back quickly in 2013. This significant increase in a short time reflects the high response rates that are predicted in the early years of the targeted marketing strategy and the fact that all meters will be in place by that time.

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[42] This does not mean that the rates are not available to everyone, just that we assume PG&E will not actively market to customers that are likely to provide very little benefit in the form of meaningful load response.

Table 4-7
SmartRate/PDP Enrollment over the Forecast Horizon
by Local Capacity Area

Forecast Year	Local Capacity Area							All
	Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
2010	20,636	7,867	7,226	8,660	20,356	12,896	4,143	81,784
2011	25,011	15,114	12,399	8,802	29,063	21,517	10,815	122,721
2012	12,378	14,087	11,051	3,917	14,919	19,506	10,937	86,795
2013	24,794	22,054	17,009	6,863	26,710	27,129	17,845	142,404
2014	34,964	25,244	18,241	10,590	31,009	29,426	20,130	169,604
2015	44,633	27,919	19,308	14,212	34,710	30,925	21,865	193,572
2016	55,566	30,075	19,967	18,346	39,838	31,985	23,334	219,111
2017	65,689	31,963	20,378	22,267	44,550	32,608	24,454	241,909
2018	74,922	33,416	20,721	25,722	48,737	33,137	25,319	261,974
2019	82,934	35,050	21,319	28,850	52,454	33,937	26,257	280,801
2020	90,124	37,032	22,196	31,641	55,599	35,244	27,402	299,238

Table 4-8 shows the annual estimated enrollment by load impact category. As discussed in section 3, a regression model was developed to predict load impacts as a function of observable customer and neighborhood characteristics in order to predict whether customers are likely to have high or low load reduction performance. The targeting focuses on customers that provide higher load reductions, though not exclusively. A customer with a smaller expected load reduction (e.g., smaller loads from a household without air conditioning), may be targeted if their likelihood of enrollment is high. The growth among customers with larger projected load reductions (over 0.50 kW) is expected to occur in the next few years and taper off thereafter, with focus shifting to customers that do not provide the same magnitude of load reduction. In addition, in later years, a substantial share of new enrollments replenishes the program from account turnover. Because of the targeted approach, load impacts from new enrollees are expected to be higher than the impacts seen in 2008 and 2009.

Table 4-8
SmartRate/PDP Enrollment over the Forecast Horizon
by Estimated Load Reduction Performance

Forecast Year	Estimated Impacts (based on high performance model)					Total
	0 to 0.25 kW	0.25 to 0.50 kW	0.50 to 0.75 kW	0.75 to 1.00 kW	1.00 kW or more	
2010	28,909	28,558	12,690	5,676	5,951	81,784
2011	31,202	41,808	24,223	12,237	13,252	122,721
2012	17,873	28,899	19,158	9,933	10,933	86,795
2013	30,900	48,927	30,849	15,261	16,467	142,404
2014	45,111	58,451	33,907	15,706	16,428	169,604
2015	59,857	66,004	35,565	15,823	16,324	193,572
2016	75,448	73,705	37,384	16,123	16,450	219,111
2017	90,141	80,038	38,666	16,424	16,640	241,909
2018	103,632	85,192	39,784	16,604	16,763	261,974
2019	116,039	89,890	40,875	16,945	17,051	280,801
2020	127,600	94,379	42,152	17,512	17,595	299,238

4.2. TOU ENROLLMENT PROJECTIONS

As discussed in Section 2 (and in more detail in Volume 1), TOU rate E7 is closed to future enrollment and PG&E has no plans to actively market TOU rate E6. As such, cumulative enrollment estimates for these tariffs in each year were simply based on what enrollment was in the prior year minus attrition. The annual attrition rate of 3.39% was derived based on a review of attrition rates for customers in the tariff in 2008 and 2009. Recall from prior discussion that the estimates of enrollment and impacts contained in this report pertain only to standard metered E6 and E7 customers, not the substantial number of net metered E6 and E7 customers that are currently on each tariff and are likely to have some form of distributed generation such as rooftop solar. Table 4-9 summarizes the enrollment projections for TOU for each forecast year. It includes all E6 and E7 customers that are not net metered.

Table 4-9
Enrollment Estimates for TOU Tariffs E6 and E7 (combined)

Year	Greater Bay Area	Greater Fresno	Humboldt	Kern	Northern Coast	Sierra	Stockton	Other	All
2010	24,752	6,746	1,920	1,610	70	13,415	6,718	11,592	66,823
2011	23,913	6,517	1,855	1,556	68	12,960	6,490	11,199	64,558
2012	23,102	6,296	1,792	1,503	66	12,521	6,270	10,819	62,369
2013	22,319	6,083	1,731	1,452	64	12,097	6,058	10,453	60,255
2014	21,562	5,876	1,672	1,403	61	11,686	5,852	10,098	58,212
2015	20,831	5,677	1,616	1,355	59	11,290	5,654	9,756	56,239
2016	20,125	5,485	1,561	1,309	57	10,908	5,462	9,425	54,332
2017	19,443	5,299	1,508	1,265	55	10,538	5,277	9,106	52,490
2018	18,784	5,119	1,457	1,222	53	10,181	5,098	8,797	50,711
2019	18,147	4,946	1,408	1,181	52	9,835	4,925	8,499	48,992
2020	17,532	4,778	1,360	1,141	50	9,502	4,758	8,211	47,331

4.3. RESIDENTIAL SMARTAC ENROLLMENT PROJECTIONS

As mentioned in section 2, in August 2009 PG&E submitted a request to the CPUC to modify the goals and budgets for SmartAC. In this document, PG&E proposed a target of 206,000 SmartAC residential customers by year-end 2011, providing a peak load impact of 209 MW. The enrollment estimates used here are the same as those that underlie the load impact estimates contained in the August 2009 filing. These estimates are based on a significant shift in marketing methods and strategies from those that were used in the past, as delineated in both the 2009 update filing and the SmartAC 2009 Annual Report.[43] While FSC developed a model of SmartAC enrollment as a function of promotional features and customer characteristics based on 2009 direct mail marketing and enrollment data, the model was not used because it could not capture the impact of some of the new promotional methods and direction that PG&E will use in 2010 and 2011, including PG&E's new psychometric targeting, the SmartAC Affiliate Program, the Refer-a-Friend Program and others.

[43] *Annual Report on Pacific Gas and Electric Company's 2009 SmartAC™ Program*. December 31, 2009.

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It should also be noted that the enrollment projections presented here ignore the potentially very significant effect that a Peak Time Rebate program could have on SmartAC enrollment. PG&E filed testimony in the PTR proceeding on February 26th.[44] In this filing, PG&E proposed a two-tiered PTR program, in which customers who are also enrolled in SmartAC and agree to have their air conditioners cycled on PTR days would be paid a higher incentive than customers who do not agree to have their air conditioner controlled. If this program is approved, it could significantly increase enrollment in SmartAC. The CPUC is expected to rule on this application sometime in late in 2010. The impact of PTR on SmartAC enrollment will be factored into future impact evaluations.

As of January, 2010, SmartAC had 124,000 residential customers. This is an increase of 16,000 over June 2009. Table 4-10 shows projected SmartAC residential enrollment by local capacity area and month for 2010 and 2011. Note that as of January 2010, the Northern Coast and Sierra LCAs had already exceeded their year-end 2011 target, so we projected zero growth for those areas.

Table 4-10
Projected Cumulative Residential SmartAC Enrollment by Month[45]

Year	Month	GREATER BAY AREA	GREATER FRESNO	KERN	NORTHERN COAST	SIERRA	STOCKTON	OTHER	TOTAL
2010	January	40,822	26,542	3,369	4,550	13,818	14,729	20,373	124,203
	February	41,621	27,597	3,996	4,550	14,126	15,194	20,785	127,868
	March	42,419	28,652	4,622	4,550	14,434	15,658	21,197	131,534
	April	43,218	29,707	5,249	4,550	14,743	16,123	21,609	135,199
	May	44,017	30,762	5,876	4,550	15,051	16,588	22,022	138,865
	June	44,815	31,817	6,502	4,550	15,359	17,053	22,434	142,530
	July	45,614	32,873	7,129	4,550	15,667	17,517	22,846	146,196
	August	46,413	33,928	7,756	4,550	15,975	17,982	23,258	149,861
	September	47,212	34,983	8,382	4,550	16,283	18,447	23,670	153,527
	October	48,010	36,038	9,009	4,550	16,592	18,912	24,082	157,192
	November	48,809	37,093	9,636	4,550	16,900	19,376	24,494	160,858
	December	49,608	38,148	10,262	4,550	17,208	19,841	24,906	164,523
2011	January	50,406	39,203	10,889	4,550	17,516	20,306	25,319	168,189
	February	51,205	40,258	11,515	4,550	17,824	20,771	25,731	171,854
	March	52,004	41,313	12,142	4,550	18,132	21,235	26,143	175,520
	April	52,802	42,368	12,769	4,550	18,441	21,700	26,555	179,185
	May	53,601	43,423	13,395	4,550	18,749	22,165	26,967	182,851
	June	54,400	44,478	14,022	4,550	19,057	22,630	27,379	186,516
	July	55,199	45,534	14,649	4,550	19,365	23,094	27,791	190,182
	August	55,997	46,589	15,275	4,550	19,673	23,559	28,203	193,847
	September	56,796	47,644	15,902	4,550	19,981	24,024	28,616	197,513
	October	57,595	48,699	16,529	4,550	20,290	24,489	29,028	201,178
	November	58,393	49,754	17,155	4,550	20,598	24,953	29,440	204,844
	December	59,192	50,809	17,782	4,550	20,906	25,418	29,852	208,509

[44] A.10-02-028 2010 Rate Design Window, Peak Time Rebate for Approval of funding request for years 2010-2013.
[45] The total of 208,500 is slightly higher than the projected enrollment of 206,000 included in PG&E's SmartAC update filing. This results from the fact that the enrollment estimates presented in the filing for the Northern Coast and Sierra LCAs were already exceeded by the end of 2009. We held those values constant over the forecast horizon.

4.4. NON-RESIDENTIAL SMARTAC ENROLLMENT PROJECTIONS

Enrollment estimates for non-residential customers were developed by another contractor, The Brattle Group (TBG). Enrollment is expected to increase from the current level of around 1,000 customers to 6,900 customers by the end of 2012 and then stay at that level for the remainder of the forecast period.

Table 4-11
Enrollment Projections for Non-Residential SmartAC

Day Type	Year		
	2010	2011	2012-2020
May Peak Day	2,357	5,138	6,898
June Peak Day	2,549	5,404	6,898
July Peak Day	2,754	5,693	6,898
August Peak Day	2,965	5,973	6,898
September Peak Day	3,188	6,271	6,898
October Peak Day	3,406	6,576	6,898

5. RESIDENTIAL SMARTRATE/PDP LOAD IMPACT ANALYSIS

This report section presents ex ante load impact estimates for the residential SmartRate tariff and its successor, PDP. The estimates for each LCA and for the service territory as a whole are based on customer specific impacts under a standard set of 1-in-2 and 1-in-10 year weather conditions and the enrollment forecasts for each LCA developed by FSC as discussed in Section 4. The enrollment estimates are based on targeting high value customers for participation in SmartRate in 2010 and PDP thereafter. Currently there are two regulatory proceedings underway involving default residential Peak Day Pricing and default residential Peak Time Rebates. The two proceeding are not factored into the ex-ante impacts because the outcome has not yet been determined. Ultimately, the outcomes of those proceedings could significantly change customer enrollment, recruitment strategy, and the ex-ante load impacts.

Although the ex-ante analysis is similar at a conceptual level to the 2009 analysis, there are several significant differences. Specifically:

- The ex-ante estimates rely on the 2009 season regression based customer impact models underlying the ex post impacts for the SmartRate tariff reported in Volume 1. Using the SmartRate impact models to predict for PDP is appropriate given the recent ruling by the CPUC directing PG&E to implement Alternative 1 of the two PDP options filed by PG&E. The peak period price on critical peak days for PDP is similar to that of SmartRate, and the robust sample of roughly 25,000 current SmartRate customers made this approach preferable to what was done last year, which developed ex ante estimates based on the demand models taken from the California Statewide Pricing Pilot. This approach was also appropriate because of the extremely modest price differential on non-PDP days that exists in the PDP tariff. The impact of this price differential on non-PDP days is so small that it was not worth estimating, which allowed us to use the more robust SmartRate impact models to forecast for event days rather than the SPP models.

- The reference loads were predicted using the 2009 regressions from the ex-post analysis with the standard 1-in-2 and 1-in-10 weather conditions. The percent load impacts were calculated based on actual customer percent load reductions in 2009 for similar customers in similar geographic regions. The percent load impacts were calculated for six local capacity areas and for six load responsiveness categories. They were subsequently applied to the regression estimated reference loads. This approach was used because it was grounded on actual, observed load impacts that had been extensively validated. In some instances, particularly during non-summer months, the ex-ante weather conditions were outside of the range experienced in 2009 and, as a result, the regression impact variables – which were sensitive to weather conditions – yielded implausible estimates of percent load reductions for several months. At the time this report was written, empirical data on residential percent load response for the months of October through April were not available for SmartRate. As a result, impacts for those months should be used cautiously.

- The 1-in-2 and 1-in-10 year weather conditions used here are different from those used last year. As discussed in Appendix C, the 1-in-10 and 1-in-2 weather conditions were recalculated to better align with the applications of DR in resource adequacy, long term planning and benefit cost analysis. The prior approach relied on a single proxy year to reflect weather conditions for each year type. Given the variation in heat waves, an extreme weather year can have a few relatively hot periods while being relatively cool the rest of the year. In contrast, this year, the weather conditions were selected based on the driver of system demand and rather than reflect the idiosyncrasies in weather of a particular year, they describe the conditions that occur on monthly system peak days under normal (1-in-2) and more extreme (1-in-10) weather conditions.

- The aggregate impact estimates reflect the requirement ordered by the CPUC to offer all residential customers the option of being billed according to the PDP peak price on alternating days rather than on every event day. This option is intended to give residential customers a hedge against large variation in bills in months that have a relatively large number of event days. If a customer does not indicate a clear choice when enrolling in the PDP tariff, the default option is for every-day event notification and billing. PG&E assumes that 70% of PDP enrollees will select the default option and the remainder will select the alternating day option. The aggregate load impact estimates account for the difference between the number of enrolled and activated participants. For any given event, all every-day option customers and half of the alternating-day option customers can be activated. As a result, aggregate load impacts are 85% of what could be attained if all enrolled participants were jointly activated. In the tables presented in the remainder of this section, all aggregate tables factor this requirement in. Tables that present average impacts per customer assume that all customers are activated.

- As discussed previously, the enrollment estimates presented here incorporate methods for improving marketing effectiveness and targeting customers based on the combination of high load reduction potential and high probability of enrolling. It should be noted that there is an inherent tension between customers that can provide the most load reduction and the likelihood that a customer will enroll on a dynamic tariff. In other words, customers that can provide the most load reduction have unfavorable load shapes for time varying pricing, particularly if an underlying weekday time varying rate structure is incorporated and, therefore, are less inclined to enroll in the program. The projections made here factor in both the attractiveness of a customer from the perspective of potential load drop and the likelihood of enrollment as part of the targeting strategy.

5.1. SMARTRATE/PDP EX ANTE LOAD IMPACT ESTIMATES

Given that there are 13 day types in each year (e.g., the typical event day plus the monthly system peak day for each month of the year), eight LCA regions plus the service territory as a whole, two weather years, eleven forecast years, and two customer groupings (e.g., average and aggregate), more than 4,500 distinct sets of estimates are needed to meet the CPUC load impact requirements. Selected tables and some additional summary values are presented in the remainder of this section.

Table 5-1 summarizes the projected program load reduction for SmartRate/PDP for each forecast year under 1-in-2 and 1-in-10 year weather conditions. The table shows the average load reduction across the five hour event period for a typical event day. The table contains a significant amount of information that underlies the aggregate load impacts presented in the sixth column, which grow from roughly 43 MW in 2010 under 1-in-2 year weather conditions to more than 121

MW by 2020. Based on 1-in-10 year weather conditions, the aggregate impacts grow from approximately 53 MW in 2010 to almost 147 MW in 2020. Underlying both sets of estimates are the enrollment projections discussed in Section 4, which grow from roughly 82,000 customers in 2010 to almost 300,000 customers in 2020. Importantly, the annual estimates reflect a drop in enrollment in 2012, following the end of the one year bill protection period for SmartRate enrollees who are defaulted onto PDP in early 2010. Enrollment is estimated to fall from 122,721 in 2011 to 86,795 in 2012, and then to more than triple by 2020. Aggregate load impact estimates follow a similar pattern, dropping from 67 MW in 2011 to 52 MW in 2012, and then growing by more than a factor of 2 by 2020. The difference in the growth rates for enrollment and load reduction reflects the marketing strategy outlined above, in which high load impact, high enrollment potential customers are recruited in the early years while lower impact customers are enrolled in the later years. This strategy is reflected in the fall in the percent load reduction across years shown in the seventh column in the table and in the drop in the saturation of central air conditioning underlying the load impacts shown in the last column in the table.

Table 5-1
Aggregate Ex-Ante Load Impacts for SmartRate/PDP by Year
(Hourly Average Reduction in MW Over the Five Hour Peak Period from 2 to 7 pm)

System Conditions	Year	# of Accounts	Avg. Reference Load (MW 2-7 pm)	Average Estimated Load with DR (MW 2-7 pm)	Load Impact (MW 2-7 pm)	% Load Reduction (2-7 pm)	Avg. Temp. (F)	Central AC (%)
1-in-2 Typical Event Day	2010	81,784	154.7	111.4	43.3	28.0%	95.4	49.8
	2011	122,721	219.0	152.2	66.9	30.5%	96.3	55.8
	2012	86,795	168.4	116.8	51.6	30.6%	97.1	60.4
	2013	142,404	267.8	186.5	81.3	30.4%	96.8	59.7
	2014	169,604	303.7	215.0	88.7	29.2%	96.3	57.5
	2015	193,572	333.4	239.1	94.3	28.3%	95.9	55.7
	2016	219,111	364.1	263.3	100.8	27.7%	95.6	54.0
	2017	241,909	390.7	284.3	106.4	27.2%	95.3	52.7
	2018	261,974	413.5	302.3	111.1	26.9%	95.1	51.6
	2019	280,801	436.0	320.1	116.0	26.6%	95.0	50.8
	2020	299,238	459.9	338.6	121.4	26.4%	94.9	50.3
1-in-10 Typical Event Day	2010	81,784	185.6	133.1	52.5	28.3%	98.5	49.8
	2011	122,721	264.3	183.1	81.3	30.7%	99.3	55.8
	2012	86,795	203.2	140.7	62.6	30.8%	100.2	60.4
	2013	142,404	323.5	224.7	98.7	30.5%	99.9	59.7
	2014	169,604	366.4	258.7	107.7	29.4%	99.4	57.5
	2015	193,572	401.6	287.3	114.3	28.5%	99.1	55.7
	2016	219,111	438.1	316.1	122.0	27.9%	98.8	54.0
	2017	241,909	469.7	341.0	128.7	27.4%	98.6	52.7
	2018	261,974	496.8	362.4	134.4	27.1%	98.4	51.6
	2019	280,801	523.5	383.4	140.2	26.8%	98.3	50.8
	2020	299,238	551.9	405.3	146.6	26.6%	98.2	50.3

Table 4-8 in Section 4 showed the distribution of enrollment by load impact expectation underlying the aggregate impact estimates summarized in Table 5-1. As seen, enrollment is much more heavily weighted toward the high-impact bins in the early years compared to the later years. For example, in 2011, 11% of enrolled customers are predicted to provide more than 1 kW in load reduction, while only 25% of the participant population is in the lowest response category, where customers are estimated to provide less than 0.25 kW in load reduction on a typical event day. In contrast, by 2020, only 6% of the participant population is estimated to provide load reductions exceeding 1 kW while 42% fall into the low response category.

Another detailed view of the underlying enrollment patterns is provided in Table 5-2, which shows the enrollment by LCA and expected load impact bin for two years, 2012 and 2020. The year 2012 is shown as it is the first year that reflects the drop in enrollment that is expected to result from the transition from SmarRate to PDP following the end of the bill protection period that goes into effect in early 2011. As discussed in Section 4, it is expected that a large number of SmartRate customers who are defaulted onto PDP in the beginning of 2011 will leave the program after the bill protection period because of the difference in the revenue neutrality underlying the SmartRate and PDP tariff designs.

Table 5-2
SmartRate/PDP Enrollment by LCA and Estimated Load Reduction Amount

Forecast Year	Estimated Load Reduction[1]	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
2012	0 to 0.25 kW	5,151	2,023	2,014	1,377	3,028	2,729	1,554	17,876
	0.25 to 0.50 kW	4,936	3,645	2,724	1,642	5,298	7,025	3,628	28,899
	0.50 to 0.75 kW	1,083	3,700	2,620	393	3,478	4,979	2,905	19,157
	0.75 to 1.00 kW	447	2,214	1,643	154	1,596	2,326	1,550	9,933
	1.00 kW or more	761	2,505	2,050	351	1,519	2,447	1,300	10,933
	Total	**12,378**	**14,087**	**11,052**	**3,918**	**14,919**	**19,507**	**10,937**	**86,798**
2020	0 to 0.25 kW	58,237	9,836	5,778	21,235	19,325	6,703	6,485	127,599
	0.25 to 0.50 kW	23,045	12,705	6,729	8,184	19,695	13,813	10,207	94,379
	0.50 to 0.75 kW	5,101	7,351	4,170	1,131	9,902	8,179	6,320	42,152
	0.75 to 1.00 kW	1,726	3,460	2,425	381	3,600	3,364	2,556	17,512
	1.00 kW or more	2,015	3,680	3,094	710	3,077	3,185	1,834	17,595
	Total	**90,124**	**37,032**	**22,195**	**31,641**	**55,599**	**35,244**	**27,401**	**299,236**

Table 5-3 shows the aggregate load impact by LCA and month for 2012, and Table 5-4 shows the same information for 2020. The distribution of aggregate impacts across LCAs in 2012 reflects two underlying factors. First, many customers who had enrolled in the SmartRate program prior to 2011 are predicted to drop off in 2012. Many of these customers were located in the Kern and Fresno LCAs, where SmartMeters were deployed first and SmartRate participants were heavily recruited. As a result of these drop outs caused by the transition from SmartRate, which was revenue neutral for high use customers, to PDP, which is revenue neutral for the average PG&E customer, the aggregate load impacts in these areas are less than they would have been had this enrollment decline not occurred. Second, the 2012 impacts reflect new recruitment of high load impact participants from other hot regions that were not recruited early, such as Sierra. Heavy participation from the much more populous Bay Area, which is much cooler and has many fewer high load reduction prospects than other regions, has not yet materialized. As seen in Table 5-4, by the end of the forecast horizon, many more customers have enrolled from other LCAs, and especially from the Bay Area.

Table 5-3
PDP Aggregate Load Impacts by LCA and Month for 2012
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	4.5	9.7	7.0	1.6	8.6	13.2	7.1	51.6
	January	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	February	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	March	3.0	3.0	1.8	1.0	3.1	5.0	2.3	19.3
	April	2.9	4.3	3.1	1.0	3.9	5.7	3.5	24.3
	May	2.8	8.5	5.9	1.0	5.8	8.9	5.0	37.9
	June	4.9	8.0	6.0	1.8	7.1	10.3	5.9	43.9
	July (Annual Peak)	5.1	12.8	8.4	1.8	10.5	15.6	8.2	62.4
	August	4.7	8.2	6.9	1.7	8.5	13.0	6.9	49.9
	September	3.4	9.1	6.2	1.2	7.7	12.3	6.4	46.3
	October	3.3	5.2	3.8	1.1	4.3	6.0	4.0	27.7
	November	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	December	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
1-in-10	Typical Event Day	5.4	12.3	8.0	2.0	10.7	15.5	8.7	62.6
	January	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	February	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	March	3.0	3.0	1.8	1.0	3.1	5.0	2.3	19.3
	April	3.1	5.5	4.1	1.1	4.4	6.2	4.1	28.5
	May	4.4	10.2	7.5	1.6	8.9	12.3	7.1	52.2
	June	6.7	11.2	7.5	2.4	9.7	13.5	8.1	59.2
	July (Annual Peak)	5.6	12.6	7.1	2.0	12.6	18.0	9.9	67.9
	August	4.5	15.0	9.8	1.7	11.7	16.6	9.1	68.4
	September	5.1	9.4	6.9	1.9	8.4	11.9	6.9	50.5
	October	3.8	7.7	5.7	1.3	7.5	11.7	6.3	44.0
	November	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	December	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6

Table 5-4
PDP Aggregate Load Impacts (MW) by LCA and Month for 2020
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	23.1	18.7	11.7	7.7	24.8	21.0	14.4	121.4
	January	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	February	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	March	17.1	5.9	3.0	5.8	9.0	8.1	4.8	53.8
	April	16.4	8.4	5.2	5.6	11.4	9.1	7.2	63.3
	May	16.4	16.4	9.9	5.6	17.1	14.3	10.1	89.6
	June	25.2	15.5	10.1	8.4	20.6	16.4	12.0	108.1
	July (Annual Peak)	25.5	24.8	14.0	8.4	30.4	24.9	16.6	144.6
	August	24.2	15.9	11.6	8.0	24.5	20.7	14.0	118.9
	September	18.4	17.5	10.4	6.2	22.4	19.5	13.1	107.6
	October	18.9	10.0	6.5	6.4	12.7	9.7	8.2	72.5
	November	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	December	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
1-in-10	Typical Event Day	27.3	23.8	13.4	9.0	30.9	24.6	17.8	146.6
	January	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	February	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	March	17.1	5.9	3.0	5.9	9.0	8.1	4.8	53.8
	April	17.3	10.6	7.0	5.9	13.0	9.9	8.4	72.0
	May	23.0	19.8	12.7	7.7	26.0	19.6	14.5	123.1
	June	33.2	21.7	12.7	11.0	27.9	21.5	16.4	144.3
	July (Annual Peak)	28.0	24.5	12.0	9.2	35.9	28.6	20.3	158.4
	August	23.3	29.0	16.3	7.7	34.0	26.3	18.5	155.3
	September	26.0	18.1	11.6	8.6	24.5	19.0	14.1	122.0
	October	20.7	14.9	9.6	6.9	21.7	18.7	12.8	105.3
	November	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	December	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3

Tables 5-3 and 5-4 also show how load impacts vary across months. Concentrating on the summer period from May through October in 2020 (Table 5-4), the aggregate impacts peak at 145 MW in July based on 1-in-2 year weather conditions and 158 MW based on 1-in-10 year conditions. October has the lowest load impacts based on both weather conditions and it is much lower based on 1-in-2 year weather (73 MW) than it is based on 1-in-10 year weather (105 MW).

The winter estimates, which do not vary from November through March, should be used with extreme caution. The SmartRate upon which the impact analysis was based did not have time varying rates in the winter. As such, these estimates are based on average percent reductions from the summer period for days with zero cooling degree hours, to reflect load reductions associated with usage that is unrelated to air conditioning load. They are a crude proxy for what load reductions might be during the winter period, when lighting and other factors that do not influence summer load shifting could play an important role. The willingness of consumers to shift load associated with other end uses may also have a seasonal pattern that is not captured through the approach used here. In general, there is very limited information available (not just in California but elsewhere as well) concerning what load shifting behavior might be in the winter under dynamic rates.

Tables 5-5 through 5-8 show the average reference load and load reduction over the five hour peak period for the average customer in 2012 and 2020, by LCA, month and weather year. Several things are worth noting. First, the average reference load on a typical event day is predicted to grow from 2.28 kW in 2012 (Table 5-5) to 2.76 kW in 2020 (Table 5-7) based on 1-in-2 year weather conditions. Both of these values are significantly higher than the average reference load of 2.01 kW observed across the 15 event days that were called in 2009 for the roughly 25,000 customers that are currently enrolled in SmartRate. (See Table 3-3 in Volume 1.) The difference between the ex post and ex ante estimates reflects the high value targeting strategy underlying the 2012 and 2020 ex ante estimates.[46]

Table 5-5
Reference Load for the Average PDP Customer (kW)
During the Peak Period by LCA and Month for 2012
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	1.13	2.59	2.80	1.21	2.15	2.47	2.91	2.28
	January Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	February Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	March Peak	0.83	0.81	0.70	0.85	0.78	0.94	0.97	0.85
	April Peak	0.79	1.16	1.25	0.82	1.00	1.08	1.48	1.10
	May Peak	0.79	2.26	2.36	0.81	1.49	1.68	2.06	1.71
	June Peak	1.25	2.14	2.41	1.33	1.78	1.93	2.44	1.94
	July Peak	1.25	3.43	3.32	1.35	2.62	2.93	3.36	2.75
	August Peak	1.19	2.19	2.76	1.27	2.12	2.44	2.84	2.20
	September Peak	0.90	2.41	2.48	0.94	1.94	2.30	2.65	2.06
	October Peak	0.91	1.39	1.57	0.93	1.12	1.16	1.69	1.26
	November Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	December Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
1-in-10	Typical Event Day	1.34	3.29	3.18	1.45	2.65	2.90	3.58	2.75
	January Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	February Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	March Peak	0.83	0.81	0.71	0.85	0.78	0.94	0.97	0.85
	April Peak	0.84	1.46	1.68	0.87	1.14	1.17	1.73	1.29
	May Peak	1.12	2.73	3.00	1.19	2.25	2.31	2.93	2.31
	June Peak	1.67	3.01	3.00	1.80	2.40	2.53	3.32	2.59
	July Peak	1.38	3.38	2.86	1.49	3.06	3.37	4.07	2.97
	August Peak	1.14	4.02	3.83	1.22	2.93	3.11	3.73	3.03
	September Peak	1.28	2.50	2.77	1.37	2.11	2.25	2.85	2.23
	October Peak	1.00	2.06	2.30	1.05	1.87	2.20	2.60	1.96
	November Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85
	December Peak	0.83	0.79	0.72	0.86	0.82	0.94	0.99	0.85

[46] There may also be differences in the weather conditions underlying the ex post and ex ante impact estimates.

While the reference loads grow over the forecast horizon, a comparison of the values in Tables 5-6 and 5-8 indicates that the average load reduction for the same years and event conditions based on 1-in-2 year weather conditions drops from 0.70 kW in 2012 (Table 5-6) to 0.62 kW in 2020 (Table 5-8). This reflects the shift from high value to lower value customers that is inherent in the targeting strategy that markets to the highest value customers in the early years. In 2012, for example, the average load reduction on a typical event day is roughly 31%, whereas by 2020, that value had dropped to approximately 22%.

Table 5-6
Average Load Reduction per PDP Customer (kW) During Peak Period by LCA and Month for 2012 (1-in-2 and 1-in-10 Year Weather Conditions)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	0.43	0.81	0.74	0.49	0.68	0.79	0.76	0.70
	January Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	February Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	March Peak	0.28	0.25	0.19	0.31	0.25	0.30	0.25	0.26
	April Peak	0.27	0.36	0.32	0.30	0.31	0.34	0.38	0.33
	May Peak	0.27	0.71	0.62	0.29	0.46	0.54	0.53	0.51
	June Peak	0.46	0.67	0.64	0.53	0.56	0.62	0.64	0.59
	July Peak	0.48	1.07	0.89	0.55	0.83	0.94	0.88	0.85
	August Peak	0.45	0.68	0.74	0.52	0.67	0.78	0.74	0.68
	September Peak	0.32	0.76	0.66	0.36	0.61	0.74	0.69	0.63
	October Peak	0.31	0.43	0.41	0.34	0.34	0.36	0.43	0.38
	November Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	December Peak	0.29	0.24	0.19	0.31	0.27	0.3	0.26	0.27
1-in-10	Typical Event Day	0.52	1.03	0.85	0.60	0.84	0.93	0.94	0.85
	January Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	February Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	March Peak	0.28	0.25	0.19	0.31	0.25	0.30	0.25	0.26
	April Peak	0.29	0.46	0.44	0.32	0.35	0.37	0.44	0.39
	May Peak	0.42	0.86	0.80	0.47	0.71	0.74	0.76	0.71
	June Peak	0.64	0.94	0.80	0.73	0.76	0.82	0.87	0.80
	July Peak	0.53	1.06	0.76	0.61	0.99	1.08	1.07	0.92
	August Peak	0.43	1.26	1.04	0.50	0.93	1.00	0.97	0.93
	September Peak	0.49	0.79	0.74	0.56	0.67	0.72	0.74	0.69
	October Peak	0.36	0.64	0.61	0.40	0.59	0.71	0.68	0.60
	November Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27
	December Peak	0.29	0.24	0.19	0.31	0.27	0.30	0.26	0.27

A comparison of the monthly pattern in any of the tables illustrates the strong influence of air conditioning during the summer period underlying both the reference load and load impacts in each year and set of weather conditions. For example, as seen in Table 5-5, the reference load during the peak period varies by a factor of more than 3.5 between the winter months and the peak month based on 1-in-10 weather conditions and 2012 enrollment. The influence of air conditioning can also easily be seen in any of the tables by comparing differences in reference load and load impacts across LCA regions.

Table 5-7
Average PDP Customer Reference Load (kW)
During Peak Period by LCA and Month for 2020
(1-in-2 and 1-in-10 Year Weather Conditions)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	1.81	0.98	2.44	2.73	0.95	2.04	2.34	2.76
	January Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	February Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	March Peak	0.80	0.78	0.79	0.67	0.78	0.74	0.92	0.94
	April Peak	0.96	0.75	1.11	1.22	0.74	0.97	1.03	1.42
	May Peak	1.38	0.75	2.13	2.30	0.74	1.45	1.60	1.96
	June Peak	1.60	1.07	2.03	2.35	1.05	1.70	1.83	2.31
	July Peak	2.15	1.06	3.23	3.22	1.03	2.48	2.78	3.18
	August Peak	1.76	1.02	2.07	2.68	0.99	2.02	2.31	2.69
	September Peak	1.62	0.81	2.27	2.42	0.80	1.85	2.19	2.52
	October Peak	1.12	0.88	1.31	1.54	0.87	1.09	1.11	1.61
	November Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	December Peak	0.8	0.78	0.77	0.69	0.77	0.78	0.92	0.95
1-in-10	Typical Event Day	2.17	1.14	3.10	3.09	1.10	2.50	2.74	3.40
	January Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	February Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	March Peak	0.80	0.78	0.79	0.67	0.78	0.74	0.92	0.94
	April Peak	1.10	0.78	1.39	1.65	0.77	1.11	1.12	1.65
	May Peak	1.84	0.99	2.57	2.91	0.96	2.14	2.18	2.78
	June Peak	2.11	1.36	2.84	2.91	1.32	2.28	2.40	3.15
	July Peak	2.33	1.17	3.18	2.78	1.13	2.85	3.19	3.87
	August Peak	2.33	0.99	3.77	3.70	0.96	2.78	2.95	3.54
	September Peak	1.81	1.09	2.36	2.69	1.06	2.01	2.14	2.72
	October Peak	1.58	0.92	1.95	2.24	0.90	1.79	2.09	2.47
	November Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95
	December Peak	0.80	0.78	0.77	0.69	0.77	0.78	0.92	0.95

Table 5-8
Average PDP Load Reduction per Customer (kW)
During Peak Period by LCA and Month for 2020
(1-in-2 and 1-in-10 Year Weather Conditions)

System Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	0.48	0.30	0.59	0.62	0.29	0.53	0.70	0.62
	January Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	February Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	March Peak	0.21	0.22	0.19	0.16	0.22	0.19	0.27	0.21
	April Peak	0.25	0.21	0.27	0.27	0.21	0.24	0.30	0.31
	May Peak	0.35	0.21	0.52	0.52	0.21	0.36	0.48	0.43
	June Peak	0.43	0.33	0.49	0.54	0.31	0.44	0.55	0.52
	July Peak	0.57	0.33	0.79	0.74	0.31	0.64	0.83	0.71
	August Peak	0.47	0.32	0.50	0.62	0.30	0.52	0.69	0.60
	September Peak	0.42	0.24	0.56	0.55	0.23	0.47	0.65	0.56
	October Peak	0.28	0.25	0.32	0.34	0.24	0.27	0.32	0.35
	November Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	December Peak	0.21	0.22	0.18	0.16	0.22	0.2	0.27	0.21
1-in-10	Typical Event Day	0.58	0.36	0.76	0.71	0.33	0.65	0.82	0.76
	January Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	February Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	March Peak	0.21	0.22	0.19	0.16	0.22	0.19	0.27	0.21
	April Peak	0.28	0.23	0.34	0.37	0.22	0.28	0.33	0.36
	May Peak	0.48	0.30	0.63	0.67	0.28	0.55	0.65	0.62
	June Peak	0.57	0.43	0.69	0.67	0.41	0.59	0.72	0.71
	July Peak	0.62	0.37	0.78	0.63	0.34	0.76	0.95	0.87
	August Peak	0.61	0.30	0.92	0.87	0.29	0.72	0.88	0.79
	September Peak	0.48	0.34	0.58	0.62	0.32	0.52	0.64	0.60
	October Peak	0.41	0.27	0.47	0.51	0.26	0.46	0.62	0.55
	November Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21
	December Peak	0.21	0.22	0.18	0.16	0.22	0.20	0.27	0.21

Table 5-9 shows the impact by hour for a typical event day based on 1-in-2 year weather conditions and 2012 enrollment. Table 5-10 shows the same information based on enrollment in 2020. As seen in Table 5-9, the reference load increases steadily over the five-hour event period, from roughly 1.95 kW to 2.49 kW. Both the load drop (kW) and the percent load drop vary across the hours, with the lowest load drop occurring in the first event hour but the lowest percentage load drop occurring in the final event hour from 6 pm to 7 pm when many household members are home from work and preparing the evening meal.

Table 5-9
Hourly Load Reduction for PDP Tariff For a Typical Event Day
Based on 1-in-2 Year Weather Conditions and 2012 Program Enrollment

TABLE 1: Menu options

Type of Results	Average Customer
Day Type	Typical Event Day
Weather Year	1-in-2
Forecast Year	2012
Local Capacity Area	All

TABLE 2: Event Day Information

Event Start	14:00
Event End	19:00
Total Enrolled Accounts	86,795
Total Accounts Activated	73,776
Avg. Load Reduction (2-7 pm)	0.70
% Load Reduction (2-7 pm)	31.4%

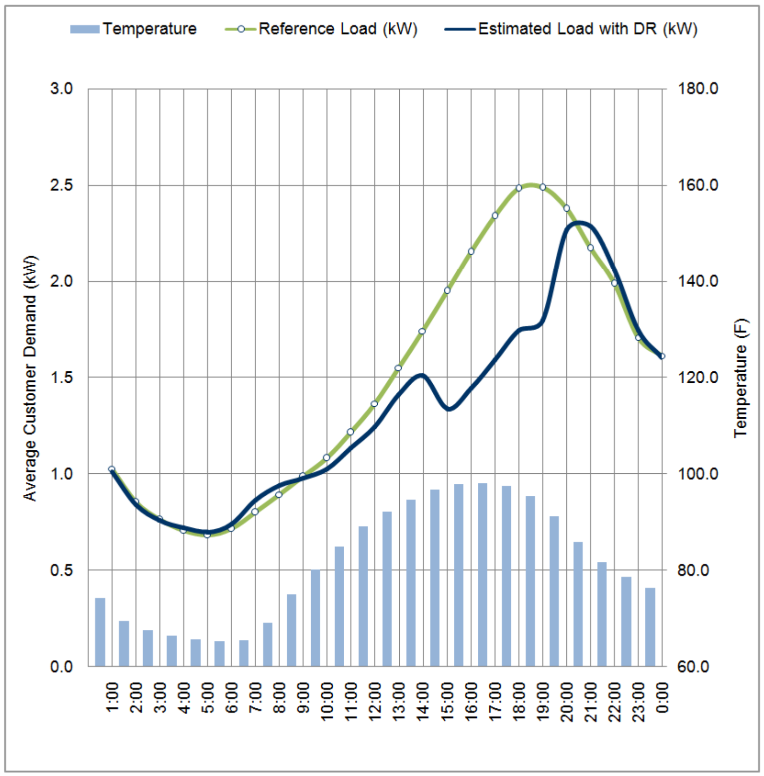

TABLE 3: Ex-Ante Load Impact Results

Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	1.03	1.01	0.02	1.8%	74.3	-0.11	-0.03	0.02	0.07	0.14
2:00	0.85	0.84	0.01	1.2%	69.5	-0.11	-0.04	0.01	0.06	0.14
3:00	0.76	0.76	0.01	0.7%	67.6	-0.12	-0.05	0.01	0.06	0.13
4:00	0.71	0.72	-0.02	-2.3%	66.5	-0.14	-0.07	-0.02	0.04	0.11
5:00	0.68	0.70	-0.02	-2.3%	65.8	-0.14	-0.07	-0.02	0.04	0.11
6:00	0.72	0.74	-0.02	-3.3%	65.3	-0.15	-0.07	-0.02	0.03	0.10
7:00	0.80	0.86	-0.06	-8.0%	65.5	-0.19	-0.12	-0.06	-0.01	0.06
8:00	0.90	0.94	-0.04	-5.0%	69.2	-0.17	-0.10	-0.04	0.01	0.08
9:00	0.99	0.98	0.01	1.0%	75.0	-0.12	-0.04	0.01	0.06	0.14
10:00	1.08	1.03	0.06	5.1%	80.2	-0.07	0.00	0.06	0.11	0.18
11:00	1.22	1.13	0.08	6.7%	85.0	-0.04	0.03	0.08	0.13	0.21
12:00	1.37	1.25	0.12	8.7%	89.2	-0.01	0.07	0.12	0.17	0.24
13:00	1.55	1.41	0.14	9.1%	92.2	0.02	0.09	0.14	0.19	0.27
14:00	1.74	1.51	0.23	13.2%	94.7	0.11	0.18	0.23	0.28	0.36
15:00	1.95	1.34	0.61	31.3%	96.8	0.48	0.56	0.61	0.66	0.73
16:00	2.16	1.45	0.71	33.0%	98.0	0.59	0.66	0.71	0.76	0.84
17:00	2.34	1.59	0.75	32.0%	98.1	0.62	0.70	0.75	0.80	0.87
18:00	2.48	1.75	0.74	29.7%	97.5	0.61	0.69	0.74	0.79	0.86
19:00	2.49	1.80	0.69	27.7%	95.4	0.57	0.64	0.69	0.74	0.82
20:00	2.38	2.27	0.11	4.6%	91.2	-0.02	0.06	0.11	0.16	0.23
21:00	2.17	2.29	-0.11	-5.3%	85.8	-0.24	-0.17	-0.11	-0.06	0.01
22:00	1.99	2.06	-0.07	-3.7%	81.6	-0.20	-0.12	-0.07	-0.02	0.05
23:00	1.71	1.74	-0.03	-2.0%	78.6	-0.16	-0.09	-0.03	0.02	0.09
0:00	1.61	1.60	0.01	0.6%	76.4	-0.12	-0.04	0.01	0.06	0.14

	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	% Daily Load Reduction	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	35.67	31.76	3.90	10.9%	130.9	3.88	3.89	3.90	3.91	3.93

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Table 5-10
Hourly Load Reduction for PDP Tariff For a Typical Event Day
Based on 1-in-2 Year Weather Conditions and 2020 Program Enrollment

TABLE 1: Menu options

Type of Results	Average Customer
Day Type	Typical Event Day
Weather Year	1-in-2
Forecast Year	2020
Local Capacity Area	All

TABLE 2: Event Day Information

Event Start	14:00
Event End	19:00
Total Enrolled Accounts	299,238
Total Accounts Activated	254,352
Avg. Load Reduction (2-7 pm)	0.48
% Load Reduction (2-7 pm)	27.1%

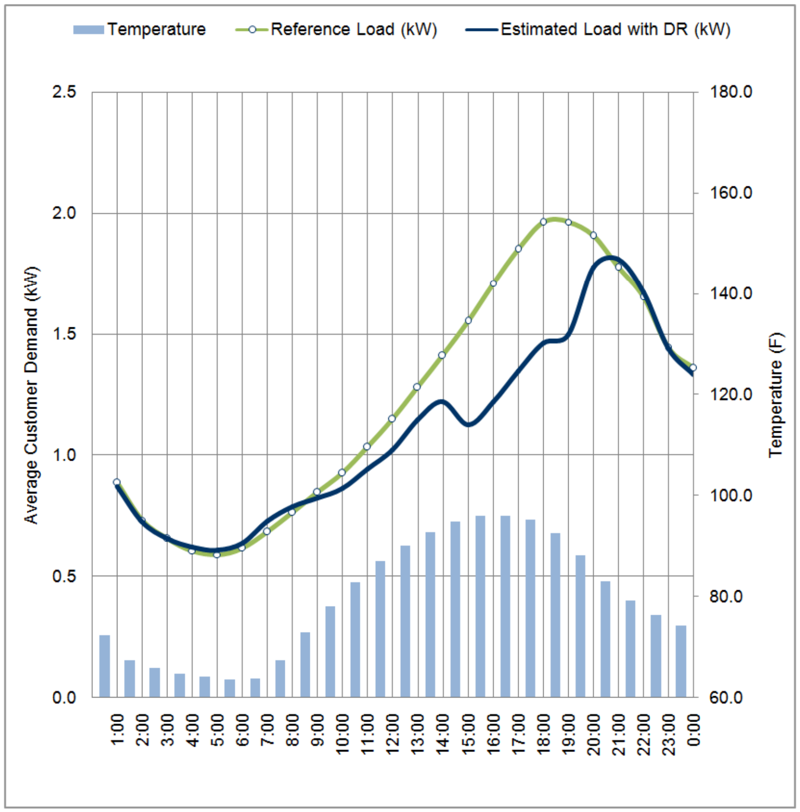

TABLE 3: Ex-Ante Load Impact Results

Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	0.89	0.87	0.02	1.9%	72.4	-0.08	-0.02	0.02	0.06	0.11
2:00	0.73	0.72	0.01	1.2%	67.5	-0.09	-0.03	0.01	0.05	0.11
3:00	0.66	0.66	0.00	0.2%	65.8	-0.10	-0.04	0.00	0.04	0.10
4:00	0.61	0.62	-0.02	-2.6%	64.8	-0.11	-0.06	-0.02	0.02	0.08
5:00	0.59	0.61	-0.02	-2.7%	64.2	-0.11	-0.06	-0.02	0.02	0.08
6:00	0.62	0.64	-0.02	-3.3%	63.6	-0.12	-0.06	-0.02	0.02	0.08
7:00	0.68	0.73	-0.04	-6.5%	63.9	-0.14	-0.08	-0.04	-0.01	0.05
8:00	0.76	0.79	-0.02	-3.1%	67.5	-0.12	-0.06	-0.02	0.02	0.07
9:00	0.85	0.82	0.02	2.7%	73.0	-0.07	-0.02	0.02	0.06	0.12
10:00	0.93	0.86	0.07	7.0%	78.1	-0.03	0.03	0.07	0.10	0.16
11:00	1.03	0.94	0.09	8.6%	82.9	-0.01	0.05	0.09	0.13	0.19
12:00	1.15	1.02	0.13	11.0%	87.0	0.03	0.09	0.13	0.17	0.22
13:00	1.28	1.14	0.14	10.6%	90.0	0.04	0.10	0.14	0.18	0.23
14:00	1.41	1.22	0.19	13.4%	92.7	0.09	0.15	0.19	0.23	0.29
15:00	1.55	1.13	0.43	27.5%	94.8	0.33	0.39	0.43	0.47	0.52
16:00	1.71	1.22	0.49	28.7%	95.9	0.39	0.45	0.49	0.53	0.59
17:00	1.85	1.35	0.50	27.1%	96.1	0.41	0.46	0.50	0.54	0.60
18:00	1.96	1.46	0.50	25.4%	95.2	0.40	0.46	0.50	0.54	0.60
19:00	1.96	1.50	0.47	23.8%	92.6	0.37	0.43	0.47	0.51	0.56
20:00	1.91	1.78	0.13	6.9%	88.2	0.03	0.09	0.13	0.17	0.23
21:00	1.78	1.81	-0.03	-1.9%	83.1	-0.13	-0.07	-0.03	0.01	0.06
22:00	1.65	1.67	-0.02	-1.2%	79.2	-0.12	-0.06	-0.02	0.02	0.08
23:00	1.44	1.44	0.00	0.0%	76.4	-0.10	-0.04	0.00	0.04	0.10
0:00	1.36	1.33	0.03	2.1%	74.4	-0.07	-0.01	0.03	0.07	0.12

	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	% Daily Load Reduction	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	29.36	26.33	3.02	10.3%	130.9	3.01	3.02	3.02	3.03	3.04

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The final estimates provided in this section show the aggregate load reductions by hour and month for 2012 and 2020. As seen in Table 5-11, aggregate load impacts based on 2012 enrollment peak between 4 and 5 pm and equal 67.1 MW on the annual system peak day under 1-in-2 year weather conditions and equal 73.2 MW based on 1-in-10 year weather conditions. By 2020, the peak hour estimates equal 153.2 MW and 168.5 MW, respectively.

Table 5-11
PDP Aggregate Impacts (MW) by Hour and Month for 2012 Enrollment
(Monthly System Peak Day)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	4.5	9.7	7.0	1.6	8.6	13.2	7.1	51.6
	January	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	February	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	March	3.0	3.0	1.8	1.0	3.1	5.0	2.3	19.3
	April	2.9	4.3	3.1	1.0	3.9	5.7	3.5	24.3
	May	2.8	8.5	5.9	1.0	5.8	8.9	5.0	37.9
	June	4.9	8.0	6.0	1.8	7.1	10.3	5.9	43.9
	July (Annual Peak)	5.1	12.8	8.4	1.8	10.5	15.6	8.2	62.4
	August	4.7	8.2	6.9	1.7	8.5	13.0	6.9	49.9
	September	3.4	9.1	6.2	1.2	7.7	12.3	6.4	46.3
	October	3.3	5.2	3.8	1.1	4.3	6.0	4.0	27.7
	November	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	December	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
1-in-10	Typical Event Day	5.4	12.3	8.0	2.0	10.7	15.5	8.7	62.6
	January	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	February	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	March	3.0	3.0	1.8	1.0	3.1	5.0	2.3	19.3
	April	3.1	5.5	4.1	1.1	4 .4	6.2	4.1	28.5
	May	4.4	10.2	7.5	1.6	8.9	12.3	7.1	52.2
	June	6.7	11.2	7.5	2.4	9.7	13.5	8.1	59.2
	July (Annual Peak)	5.6	12.6	7.1	2.0	12.6	18.0	9.9	67.9
	August	4.5	15.0	9.8	1.7	11.7	16.6	9.1	68.4
	September	5.1	9.4	6.9	1.9	8.4	11.9	6.9	50.5
	October	3.8	7.7	5.7	1.3	7.5	11.7	6.3	44.0
	November	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6
	December	3.0	2.9	1.8	1.0	3.4	5.0	2.4	19.6

[1] Factors in derate for participants that choose every other day option

Table 5-12
PDP Aggregate Impacts (MW) by Hour and Month for 2020 Enrollment
(Monthly System Peak Day)

Weather Conditions	Day Type	Local Capacity Area							All
		Greater Bay Area	Greater Fresno	Kern	Northern Coast	Other	Sierra	Stockton	
1-in-2	Typical Event Day	23.1	18.7	11.7	7.7	24.8	21.0	14.4	121.4
	January	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	February	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	March	17.1	5.9	3.0	5.8	9.0	8.1	4.8	53.8
	April	16.4	8.4	5.2	5.6	11.4	9.1	7.2	63.3
	May	16.4	16.4	9.9	5.6	17.1	14.3	10.1	89.6
	June	25.2	15.5	10.1	8.4	20.6	16.4	12.0	108.1
	July (Annual Peak)	25.5	24.8	14.0	8.4	30.4	24.9	16.6	144.6
	August	24.2	15.9	11.6	8.0	24.5	20.7	14.0	118.9
	September	18.4	17.5	10.4	6.2	22.4	19.5	13.1	107.6
	October	18.9	10.0	6.5	6.4	12.7	9.7	8.2	72.5
	November	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	December	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
1-in-10	Typical Event Day	27.3	23.8	13.4	9.0	30.9	24.6	17.8	146.6
	January	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	February	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	March	17.1	5.9	3.0	5.9	9.0	8.1	4.8	53.8
	April	17.3	10.6	7.0	5.9	13.0	9.9	8.4	72.0
	May	23.0	19.8	12.7	7.7	26.0	19.6	14.5	123.1
	June	33.2	21.7	12.7	11.0	27.9	21.5	16.4	144.3
	July (Annual Peak)	28.0	24.5	12.0	9.2	35.9	28.6	20.3	158.4
	August	23.3	29.0	16.3	7.7	34.0	26.3	18.5	155.3
	September	26.0	18.1	11.6	8.6	24.5	19.0	14.1	122.0
	October	20.7	14.9	9.6	6.9	21.7	18.7	12.8	105.3
	November	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3
	December	17.1	5.7	3.0	5.8	9.5	8.2	4.9	54.3

[1] Factors in derate for participants that choose every other day option

5.2. RECOMMENDATIONS

The analysis presented in this section and in sections 3 and 4 can be extremely useful as PG&E considers its optimal marketing strategy for PDP starting in 2011. The parametric modeling summarized in Section 4.1.2 highlights a number of factors that can impact enrollment rates, including:

- Sign up incentives have a very strong influence on customer enrollment. Using direct mail, a modest incentive of $25 can double response rates (from 2.4% to 4.9%);
- There is a strong seasonal factor in marketing dynamic rates, with take rates being much higher when marketing occurs before June than if it occurs in late summer.
- Marketing dynamic rates to customers with enabling technology dramatically increases response rates. Enrollment rates equaled 15% when SmartRate was offered to SmartAC customers without an incentive, and 24% when a $25 incentive was offered.

- Simple things like using a #10 letter (rather than a glossy brochure) and multilingual marketing materials can increase response rates.

- Soliciting the same customer multiple times can increase overall enrollment rates, but there are diminishing returns to second and third offers.

Targeting high value customers is possible using the models discussed in Section 4, but it is important to recognize the natural tension between customers that can and will provide large load reductions when enrolled on dynamic tariffs, and the likelihood that they will enroll. Customers with high air conditioning loads provide much larger load reductions than do customers without central air conditioning or those with central air conditioning that is used very little, but these same customers have a higher probability of being structural losers and, as such, a lower probability of enrolling in such programs. The ex ante forecasts presented here factor both of these important considerations into the marketing strategy and we encourage PG&E to consider a similar strategy when it develops its PDP marketing plans.

The analysis examining the incremental effect of load control for SmartRate customers should be carefully considered when developing future marketing plans. A key finding is that load control can significantly improve demand response for low responsive customers or customers that do not receive event notifications, but adds little to high responders who have already made significant reductions in air conditioning use. This suggests a careful targeting strategy for offering SmartAC to PDP customers. Having said that, there is more analysis and work to be done in this important area. This should be a key focus of the impact evaluation in 2010, when PG&E will have large samples of customers who are dually enrolled in SmartAC and SmartRate. We recommend that PG&E consider selecting a small group of customers that are enrolled in both SmartRate and SmartAC that can be operated as a control sample so that maximum insight can be gained.

We encourage PG&E to continue trying new marketing approaches and carefully tracking take rates so that the choice models estimated this year can be updated and enhanced in support of future marketing efforts.

6. RESIDENTIAL TOU RATE LOAD IMPACT ANALYSIS

This report section presents ex ante load impact estimates for the residential time of use rates, E6 and E7. The models used to predict the ex post load impacts reported in Volume 1 were also used to produce the ex ante reference loads and load impacts, presented below, based on the 1-in-2 and 1-in-10 year weather conditions. As documented in Volume 1, Section 5, the impact regression model was based on the E7 TOU rate class load research sample and a control group selected using propensity score matching.

Recall from the discussion in Section 4 that the impact estimates presented here represent the combined enrollment for standard metered E6 and E7 customers. Data do not exist to support load impact estimates for the roughly 18,000 net metered customers that are currently enrolled on the E6 and E7 tariffs. Moreover, since those customers have distributed generation, likely solar, their impacts are accounted for through evaluations of distributed generation programs.

Given that there are 24 day types in each year (e.g., the monthly system peak day and average weekday for each month for the entire year), eight LCA regions plus the service territory as a whole, two weather years, eleven forecast years, and two customer groupings (e.g., average and aggregate), more than 9,504 distinct sets of estimates are needed to meet the CPUC load impact requirements. Selected tables and some additional summary values are presented in the remainder of this section.

Table 6-1 summarizes the projected program load reduction for each forecast year under 1-in-2 and 1-in-10 year weather conditions. The values reflect the average load reduction capability across the 12-6 pm, peak period time frame. In practice, the load reductions vary from hour to hour with customer load and are generally higher for the system peak hour. Based on 1-in-2 year weather conditions, aggregate average peak period load reductions equal 44.8 MW for the roughly 67,000 customers enrolled in 2010, and fall to 31.7 MW by 2020, as enrollment drops to approximately 47,000 customers. The percent load drop does not vary from year to year because the customer mix is not forecasted to change, although attrition leads to lower aggregate impacts in later years. Because only attrition is factored into the enrollment forecast, there is less uncertainty about the characteristics of enrolled customers and, as a consequence, less uncertainty regarding the load reduction capability of the program under 1-in-2 and 1-in-10 year weather conditions for future years.

Table 6-1
Summary of Aggregate Ex-Ante Load Impacts for Residential TOU Tariffs by Year
(Average Peak Period Reduction on the Annual System Peak Day)

Weather Conditions	Year	Accounts	Avg. Reference Load (MW 12-6 pm)	Average Estimated Load with DR (MW 12-6 pm)	Load Impact (MW 12-6 pm)	% Load Reduction (12-6 pm)	Avg. Weighted Temperature (F)
1-in-2 Annual Peak	2010	66,823	180.5	135.7	44.8	24.8%	92.4
	2011	64,558	174.4	131.1	43.2	24.8%	92.4
	2012	62,369	168.5	126.7	41.8	24.8%	92.4
	2013	60,255	162.8	122.4	40.4	24.8%	92.4
	2014	58,212	157.2	118.2	39.0	24.8%	92.4
	2015	56,239	151.9	114.2	37.7	24.8%	92.4
	2016	54,332	146.8	110.4	36.4	24.8%	92.4
	2017	52,490	141.8	106.6	35.2	24.8%	92.4
	2018	50,711	137.0	103.0	34.0	24.8%	92.4
	2019	48,992	132.3	99.5	32.8	24.8%	92.4
	2020	47,331	127.8	96.1	31.7	24.8%	92.4
1-in-10 Annual Peak	2010	66,823	187.5	140.4	47.1	25.1%	93.3
	2011	64,558	181.1	135.6	45.5	25.1%	93.3
	2012	62,369	175.0	131.0	43.9	25.1%	93.3
	2013	60,255	169.0	126.6	42.5	25.1%	93.3
	2014	58,212	163.3	122.3	41.0	25.1%	93.3
	2015	56,239	157.8	118.1	39.6	25.1%	93.3
	2016	54,332	152.4	114.1	38.3	25.1%	93.3
	2017	52,490	147.2	110.3	37.0	25.1%	93.3
	2018	50,711	142.3	106.5	35.7	25.1%	93.3
	2019	48,992	137.4	102.9	34.5	25.1%	93.3
	2020	47,331	132.8	99.4	33.4	25.1%	93.3

Figure 6-1 shows estimates of hourly load impacts for the forecast year 2010 for the average customer based on 1-in-2 annual peak conditions. As seen in the figure, the hourly and percent load reductions are larger in the middle of the event period than in the first and last hours. The impacts per customer equal 0.75 kW for the 3-4 pm period when the system peak typically occurs. The average percent load reduction per customer is substantial, 31.1%, in light of the difference in peak to off-peak prices. Given the degree of customer self-selection into the program, it is not clear whether percent impacts would remain equivalent or decrease if additional customers were allowed to select this tariff. TOU customers generally shift load from the peak to the off periods as expected. However, on average, customers have lower consumption on hotter, system peak days likely because they cannot fully shift AC load since it is correlated with weather.

Figure 6-1
Average Residential Customer TOU Hourly Load Impact Estimates
Based on 2010 Enrollment
(1-in-2 Annual Peak Conditions)

TABLE 1: Menu options

Type of Results	Average Customer
Day Type	Typical Event Day
Weather Year	1-in-2
Forecast Year	2010
Local Capacity Area	All

TABLE 2: Event Day Information

Event Start	12:00
Event End	18:00
TOTAL ENROLLED ACCOUNTS	66,823
Avg. Load Reduction for Event Window	0.61
% Load Reduction for Event Window	23.0%

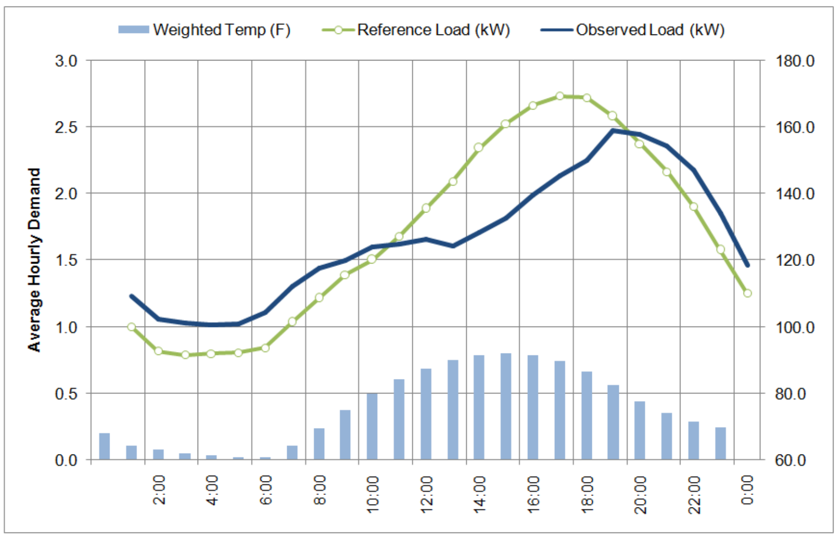

TABLE 3: Ex-Ante Load Impact Results

Hour Ending	Reference Load (kW)	Observed Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	1.00	1.23	-0.23	-22.6%	68.1	-0.37	-0.29	-0.23	-0.17	-0.08
2:00	0.82	1.06	-0.24	-29.3%	64.4	-0.39	-0.30	-0.24	-0.18	-0.10
3:00	0.79	1.03	-0.24	-30.1%	63.2	-0.38	-0.30	-0.24	-0.18	-0.09
4:00	0.80	1.01	-0.21	-26.8%	62.0	-0.36	-0.27	-0.21	-0.15	-0.07
5:00	0.81	1.02	-0.22	-26.7%	61.4	-0.36	-0.27	-0.22	-0.16	-0.07
6:00	0.84	1.11	-0.27	-31.6%	60.8	-0.41	-0.33	-0.27	-0.21	-0.12
7:00	1.03	1.31	-0.27	-26.4%	60.9	-0.42	-0.33	-0.27	-0.21	-0.13
8:00	1.21	1.44	-0.23	-18.7%	64.2	-0.37	-0.29	-0.23	-0.17	-0.08
9:00	1.39	1.50	-0.10	-7.5%	69.6	-0.25	-0.16	-0.10	-0.05	0.04
10:00	1.50	1.60	-0.10	-6.4%	75.0	-0.24	-0.15	-0.10	-0.04	0.05
11:00	1.68	1.62	0.06	3.7%	80.0	-0.08	0.00	0.06	0.12	0.21
12:00	1.89	1.66	0.23	12.1%	84.3	0.08	0.17	0.23	0.29	0.37
13:00	2.09	1.61	0.49	23.2%	87.5	0.34	0.43	0.49	0.55	0.63
14:00	2.34	1.71	0.64	27.2%	90.0	0.49	0.58	0.64	0.70	0.78
15:00	2.53	1.82	0.71	28.0%	91.5	0.56	0.65	0.71	0.77	0.85
16:00	2.66	1.99	0.68	25.3%	92.1	0.53	0.62	0.68	0.73	0.82
17:00	2.73	2.14	0.60	21.8%	91.5	0.45	0.54	0.60	0.66	0.74
18:00	2.72	2.25	0.47	17.3%	89.7	0.33	0.41	0.47	0.53	0.62
19:00	2.58	2.47	0.11	4.2%	86.7	-0.04	0.05	0.11	0.17	0.25
20:00	2.37	2.44	-0.07	-2.8%	82.5	-0.21	-0.13	-0.07	-0.01	0.08
21:00	2.16	2.36	-0.20	-9.1%	77.7	-0.34	-0.26	-0.20	-0.14	-0.05
22:00	1.90	2.18	-0.28	-14.5%	74.1	-0.42	-0.33	-0.28	-0.22	-0.13
23:00	1.58	1.85	-0.27	-17.4%	71.5	-0.42	-0.33	-0.27	-0.22	-0.13
0:00	1.25	1.46	-0.21	-17.0%	69.7	-0.36	-0.27	-0.21	-0.15	-0.07
	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	% Daily Load Reduction	Cooling Degree Hours (Base 75)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	40.71	39.87	0.84	2.1%	130.9	0.15	0.56	0.84	1.12	1.53

Table 6-2 summarizes the estimated aggregate load reduction capabilities for each forecast year and month under 1-in-2 and 1-in-10 system peak conditions. The load impacts are largest during the summer months when the ratio of peak to off-peak prices is highest. However, customers still provide a significant amount of load reduction during non-summer weekdays. The non-summer month impacts are constant because customers are primarily shifting non-weather sensitive loads. Importantly the ex-post validation confirmed that the daily load shifting for non-summer months is indeed relatively constant, although there is substantial variation by hour of day.

Table 6-2
Aggregate Ex-Ante Load Impacts (MW) for Residential TOU Customers for Monthly System Peak Days By Year and Weather Conditions (Average load impact from noon to 6 pm)

Weather Conditions	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1-in-2	2010	14.2	14.2	14.2	14.2	19.5	38.9	44.8	44.7	32.1	26.2	14.2	14.2
	2011	13.8	13.8	13.8	13.8	18.9	37.6	43.2	43.2	31.0	25.3	13.8	13.8
	2012	13.3	13.3	13.3	13.3	18.2	36.3	41.8	41.7	29.9	24.4	13.3	13.3
	2013	12.8	12.8	12.8	12.8	17.6	35.1	40.4	40.3	28.9	23.6	12.8	12.8
	2014	12.4	12.4	12.4	12.4	17.0	33.9	39.0	38.9	28.0	22.8	12.4	12.4
	2015	12.0	12.0	12.0	12.0	16.4	32.7	37.7	37.6	27.0	22.0	12.0	12.0
	2016	11.6	11.6	11.6	11.6	15.9	31.6	36.4	36.3	26.1	21.3	11.6	11.6
	2017	11.2	11.2	11.2	11.2	15.3	30.6	35.2	35.1	25.2	20.6	11.2	11.2
	2018	10.8	10.8	10.8	10.8	14.8	29.5	34.0	33.9	24.3	19.9	10.8	10.8
	2019	10.4	10.4	10.4	10.4	14.3	28.5	32.8	32.8	23.5	19.2	10.4	10.4
	2020	10.1	10.1	10.1	10.1	13.8	27.6	31.7	31.6	22.7	18.5	10.1	10.1
1-in-10	2010	14.2	14.2	14.2	14.2	35.1	55.9	47.1	44.6	44.0	31.7	14.2	14.2
	2011	13.8	13.8	13.8	13.8	33.9	54.0	45.5	43.1	42.5	30.6	13.8	13.8
	2012	13.3	13.3	13.3	13.3	32.7	52.2	43.9	41.7	41.1	29.6	13.3	13.3
	2013	12.8	12.8	12.8	12.8	31.6	50.4	42.5	40.3	39.7	28.6	12.8	12.8
	2014	12.4	12.4	12.4	12.4	30.6	48.7	41.0	38.9	38.4	27.6	12.4	12.4
	2015	12.0	12.0	12.0	12.0	29.5	47.1	39.6	37.6	37.1	26.7	12.0	12.0
	2016	11.6	11.6	11.6	11.6	28.5	45.5	38.3	36.3	35.8	25.7	11.6	11.6
	2017	11.2	11.2	11.2	11.2	27.6	43.9	37.0	35.1	34.6	24.9	11.2	11.2
	2018	10.8	10.8	10.8	10.8	26.6	42.4	35.7	33.9	33.4	24.0	10.8	10.8
	2019	10.4	10.4	10.4	10.4	25.7	41.0	34.5	32.7	32.3	23.2	10.4	10.4
	2020	10.1	10.1	10.1	10.1	24.9	39.6	33.4	31.6	31.2	22.4	10.1	10.1

Table 6-3 summarizes the average weekday load impacts for the entire day for the average TOU customer. In other words, it reflects the tariffs' conservation effects (positive values) and any potential increases in consumption (negative values) due to lower prices. Weekends are excluded. Based on the ex-post regression, the TOU tariff does not affect customer loads on weekends, when prices are flat. The program leads to a decrease in usage during peak periods, particularly during the summer. It helps reduce the need for peaking generation, lowers wholesale market prices, and potentially lowers carbon emissions (although this varies by location and supply mix). However, the net effect of the tariff is an increase in consumption of approximately 4.0% on weekdays for the average customer for a 1-in-2 year. This is equivalent to approximately 310 kWh per year.

Table 6-3
Average Residential TOU Customer Ex-Ante Load Reductions (kW) for the Average Week Day By Hour and Month for 1-in-2 Year Weather Conditions

Hour Ending	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
1:00	-0.14	-0.14	-0.14	-0.14	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.14	-0.14	**-0.20**
2:00	-0.16	-0.16	-0.16	-0.16	-0.24	-0.24	-0.24	-0.24	-0.24	-0.24	-0.16	-0.16	**-0.20**
3:00	-0.16	-0.16	-0.16	-0.16	-0.24	-0.24	-0.24	-0.24	-0.24	-0.24	-0.16	-0.16	**-0.20**
4:00	-0.16	-0.16	-0.16	-0.16	-0.21	-0.21	-0.21	-0.21	-0.21	-0.21	-0.16	-0.16	**-0.19**
5:00	-0.16	-0.16	-0.16	-0.16	-0.22	-0.22	-0.22	-0.22	-0.22	-0.22	-0.16	-0.16	**-0.19**
6:00	-0.24	-0.24	-0.24	-0.24	-0.27	-0.27	-0.27	-0.27	-0.27	-0.27	-0.24	-0.24	**-0.25**
7:00	-0.20	-0.20	-0.20	-0.20	-0.27	-0.27	-0.27	-0.27	-0.27	-0.27	-0.20	-0.20	**-0.24**
8:00	-0.08	-0.08	-0.08	-0.08	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23	-0.08	-0.08	**-0.16**
9:00	0.07	0.07	0.07	0.07	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	0.07	0.07	**-0.02**
10:00	0.08	0.08	0.08	0.08	-0.11	-0.11	-0.11	-0.11	-0.11	-0.11	0.08	0.08	**-0.02**
11:00	0.15	0.15	0.15	0.15	0.01	0.01	0.02	0.02	0.01	0.01	0.15	0.15	**0.08**
12:00	0.14	0.14	0.14	0.14	0.08	0.10	0.12	0.11	0.10	0.08	0.14	0.14	**0.12**
13:00	0.25	0.25	0.25	0.25	0.21	0.25	0.30	0.28	0.27	0.22	0.25	0.25	**0.25**
14:00	0.29	0.29	0.29	0.29	0.25	0.32	0.38	0.36	0.34	0.26	0.29	0.29	**0.30**
15:00	0.26	0.26	0.26	0.26	0.26	0.33	0.41	0.39	0.36	0.27	0.26	0.26	**0.30**
16:00	0.22	0.22	0.22	0.22	0.24	0.30	0.37	0.35	0.32	0.24	0.22	0.22	**0.26**
17:00	0.19	0.19	0.19	0.19	0.20	0.25	0.31	0.29	0.26	0.20	0.19	0.19	**0.22**
18:00	0.08	0.08	0.08	0.08	0.13	0.16	0.22	0.20	0.17	0.13	0.08	0.08	**0.12**
19:00	-0.06	-0.06	-0.06	-0.06	-0.03	-0.05	-0.03	-0.04	-0.05	0.00	-0.06	-0.06	**-0.05**
20:00	-0.12	-0.12	-0.12	-0.12	-0.11	-0.13	-0.12	-0.13	-0.13	-0.11	-0.12	-0.12	**-0.12**
21:00	-0.15	-0.15	-0.15	-0.15	-0.17	-0.20	-0.21	-0.20	-0.19	-0.17	-0.15	-0.15	**-0.17**
22:00	-0.15	-0.15	-0.15	-0.15	-0.22	-0.23	-0.26	-0.26	-0.23	-0.22	-0.15	-0.15	**-0.19**
23:00	-0.14	-0.14	-0.14	-0.14	-0.22	-0.22	-0.25	-0.24	-0.22	-0.22	-0.14	-0.14	**-0.19**
0:00	-0.14	-0.14	-0.14	-0.14	-0.23	-0.23	-0.23	-0.23	-0.23	-0.23	-0.14	-0.14	**-0.19**
Total	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.07**	**-0.06**	**-0.05**	**-0.05**	**-0.06**	**-0.07**	**-0.01**	**-0.01**	**-0.04**

Positive value indicate a load reduction, negative values indicate a load increase

6.1. RECOMMENDATIONS

The TOU impact analysis summarized above was hampered by the small sample available for the TOU and comparison group, which was drawn from a subset of PG&E's standard load research sample based on propensity score matching. In 2010, it may be possible to draw much larger TOU and comparison group samples from the growing population of interval metered customers as SmartMeters become widely deployed. We recommend drawing such a sample, stratified by LCA, wherever there is a sufficient number of properly matched customers that have had interval meters in place for at least a year, for use in the 2010 load impact evaluation.

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7. RESIDENTIAL SMART AC LOAD IMPACT ANALYSIS

This report section presents ex ante load impact estimates for the residential SmartAC program. The estimates for each LCA and for the service territory as a whole are based on the enrollment forecasts discussed in Section 4 and the average customer load impact estimates that are discussed below.

Given that there are 7 day types in each year (e.g., the typical event day plus the monthly system peak day for each month from May through October), eight LCA regions plus the service territory as a whole, two weather years, eleven forecast years, two customer groupings (e.g., average and aggregate), and two relevant scenarios (program specific and portfolio), more than 5,500 distinct sets of estimates are needed to meet the CPUC load impact requirements. Electronic versions of these tables are posted on the CALMAC web site[47]. Selected tables and some additional summary values are presented in the remainder of this section.

7.1. EX ANTE AVERAGE CUSTOMER LOAD IMPACT METHODOLOGY

In early 2009, PG&E contracted with FSC to deploy an end-use load research sample among a representative sample of customers participating in SmartAC and similar non-participating customers equipped with central air conditioning. The sample design, operational plan and evaluation plan for this load research sample were documented in a draft evaluation plan presented to the Demand Response Measurement and Evaluation Committee (DRMEC) for review on June 29, 2009. Upon peer review, minor revisions were made and included in the final evaluation plan dated July 31, 2009. Data from the load research sample were to be used for estimating the ex ante load impacts for both residential and non-residential SmartAC participants.

PG&E, in conjunction with FSC and Cooper Power Systems (host of the Master Station Software System, Yukon® that is used to operate the control switches and PCTs), developed a cycling operational plan designed to determine load impacts under different optional air conditioning control strategies and time periods over a variety of weather conditions. Unfortunately, when Cooper Power Systems moved the device data from Yukon's general population in the database to the M&E sample group, human error intervened. As a result, the M&E subset devices never received control signals during called M&E events.[48] The error was not discovered until after the end of the control season when data from the load research end-use recorders were downloaded for analysis. As a result, air conditioning load data exist for the M&E sample, but the data do not reflect any load control event response activity. These data can be used to estimate reference loads for program participants, but not load impacts.

In light of the above problem with the 2009 M&E sample, the ex ante load impact estimates presented here are based on analysis of the 2008 M&E sample, the same sample data that were used to produce ex ante impact estimates for the 2008 evaluation.[49] The analysis supporting this

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[47] www.calmac.org
[48] The error impacted the M&E sample group of roughly 630 devices only and did not affect the general SmartAC program device population nor other load research samples such as those used for the Ancillary Services Pilot operations.
[49] See Stephen S. George, Josh Bode and Matt Mercurio. *2008 Load Impact Evaluation for PG&E's SmartRate, SmartAC and Residential TOU Programs. Final Report.* May 1, 2009. Prepared for Pacific Gas

year's ex ante load impact estimates differs from what was used last year in that this year's analysis is based on the regression methodology summarized and documented in Appendix D. Last year's estimates were based on an alternative, engineering-regression methodology. The two approaches produce quite similar results for both ex post estimation and when ex ante estimates are developed using the same weather value inputs. While there are differences between last year's and this year's average impact estimates for 1-in-2 and 1-in-10 year weather conditions, these differences are due almost entirely to differences in the weather year input values.

The load impact estimates presented below are based on several assumptions, including:

- The current share of customers that have PCTs and switches (20% for PCTs, 80% for switches) is held constant over the forecast horizon;

- Due to improved cycling and more aggressive set-back strategies, future impacts are assumed to be 15% larger than in 2008 in most instances;[50]

- The marketing strategy will achieve the year-end 2011 target as discussed in Section 4.

7.1.1. Ex Ante Load Impacts for Residential SmartAC

Figure 7-1 shows estimates of hourly load impacts for the forecast year 2012 (the first year after which SmartAC enrollment stops changing)[51] for the average customer based on 1-in-2 year weather conditions for a program specific scenario. The hourly load reduction varies across the event period from a low of 0.46 kW in the first event hour to a high of 0.71 kW in the third event hour. The reference load climes steadily across the four hour event period, from a low of 1.25 kW in the first hour to a high of 1.73 kW in the last event hour. The percent reduction in this last hour, at 37%, is lower than in the prior two hours, so that the absolute reduction in hour four is less than in hour three, when the reference load is lower but the percent load reduction is higher. The average percent reduction across the four-hour period is 39%.

Pacific Gas& Electric Co. See also KEMA. *Pacific Gas & Electric SmartAC™ 2008 Residential Ex Post Load Impact Evaluation and Ex Ante Load Impact Estimates.* Final Report. March 31, 2009.

[50] The evidence supporting the 15% increase over estimated load using the 2008 load research data was provided in last year's load impact evaluation report cited in the previous footnote. This year, the adjustment was applied in a slightly different manner. The estimated percent impact for each LCA and month was adjusted upward by 15% (not 15 percentage points) unless that adjustment pushed the average percent reduction above 50% (e.g., the maximum cycling strategy), in which case the percent reduction was set equal to 50%. See Table 7-3 later in this section for the average percent reductions after making this adjustment.

[51] Recall from the discussion in Section 4 that, given the current regulatory uncertainty associated with the PTR and default PDP filings for residential customers, any forecast of SmartAC enrollment after 2012 could be potentially very misleading. As such, we held the forecast constant at the level achieved by the end of the current program budget cycle (end of 2011) over the forecast horizon, except for a small number of dual enrolled customers discussed in Section 4 that are not included in the program specific forecast presented here for reasons discussed in Section 4.

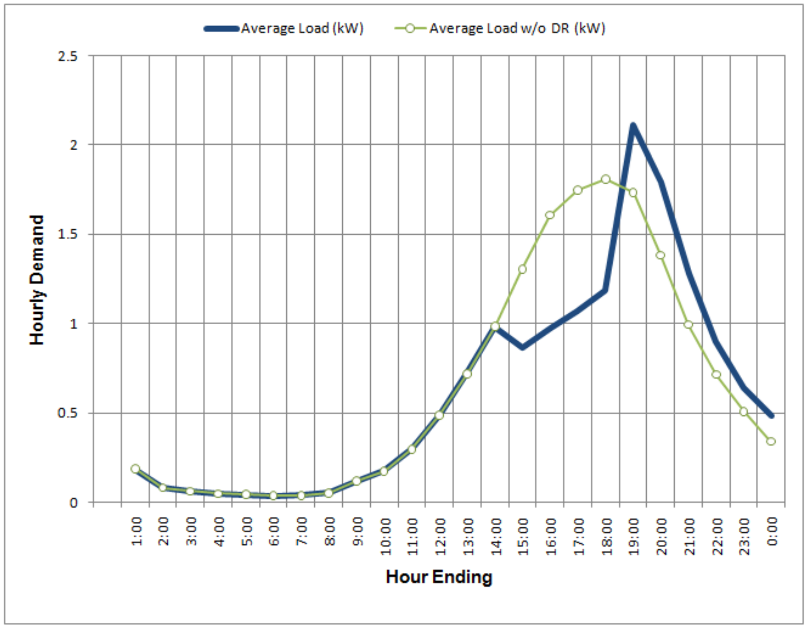
Figure 7-1
Residential SmartAC Load Impact Estimates for the Average Customer for 2012
Typical Event Day, 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Per Customer
Portfolio or Program Specific Impacts	Program specific
Local Capacity Area	All
Day type	Typical Event Day
Weather Year	1-in-2
Year	2012

TABLE 2: Event Day Information

Event Start	2:00 PM
Event End	6:00 PM
Avg. Load Reduction for Event Window	0.59
% Load Reduction for Event Window	37%
Forecast Participants	209,893
Forecast Devices	232,258



Hour Ending	Average Load w/o DR	Average Load	Load Impact	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	0.19	0.19	0.00	0.0%	77.1	0.00	0.00	0.00	0.00	0.00
2:00	0.08	0.08	0.00	0.0%	70.2	0.00	0.00	0.00	0.00	0.00
3:00	0.06	0.06	0.00	0.0%	68.2	0.00	0.00	0.00	0.00	0.00
4:00	0.05	0.05	0.00	0.0%	66.3	0.00	0.00	0.00	0.00	0.00
5:00	0.04	0.04	0.00	0.0%	65.2	0.00	0.00	0.00	0.00	0.00
6:00	0.04	0.04	0.00	0.0%	64.5	0.00	0.00	0.00	0.00	0.00
7:00	0.04	0.04	0.00	0.0%	64.4	0.00	0.00	0.00	0.00	0.00
8:00	0.05	0.05	0.00	0.0%	68.4	0.00	0.00	0.00	0.00	0.00
9:00	0.12	0.12	0.00	0.0%	74.5	0.00	0.00	0.00	0.00	0.00
10:00	0.17	0.17	0.00	0.0%	80.0	0.00	0.00	0.00	0.00	0.00
11:00	0.30	0.30	0.00	0.0%	85.1	0.00	0.00	0.00	0.00	0.00
12:00	0.49	0.49	0.00	0.0%	89.7	0.00	0.00	0.00	0.00	0.00
13:00	0.72	0.72	0.00	0.0%	93.4	0.00	0.00	0.00	0.00	0.00
14:00	0.98	0.98	0.00	0.0%	96.2	0.00	0.00	0.00	0.00	0.00
15:00	1.30	0.86	0.44	33.8%	98.8	0.42	0.43	0.44	0.45	0.46
16:00	1.61	0.97	0.63	39.4%	100.3	0.61	0.62	0.63	0.64	0.65
17:00	1.75	1.07	0.67	38.6%	100.4	0.65	0.67	0.67	0.68	0.69
18:00	1.81	1.19	0.62	34.4%	99.6	0.60	0.61	0.62	0.63	0.64
19:00	1.73	2.11	-0.38	-21.7%	97.5	-0.40	-0.38	-0.38	-0.37	-0.36
20:00	1.38	1.79	-0.41	-29.3%	93.2	-0.43	-0.41	-0.41	-0.40	-0.38
21:00	0.99	1.28	-0.29	-29.0%	87.7	-0.31	-0.30	-0.29	-0.28	-0.27
22:00	0.72	0.90	-0.18	-25.4%	83.5	-0.20	-0.19	-0.18	-0.17	-0.16
23:00	0.51	0.64	-0.13	-26.2%	81.0	-0.15	-0.14	-0.13	-0.12	-0.11
0:00	0.34	0.48	-0.14	-42.7%	79.0	-0.17	-0.15	-0.14	-0.14	-0.12
	Total Enery Use w/o DR	Observed Energy	Change in Energy	% Daily Load	Cooling Degree	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	15.47	14.63	0.84	-5.4%	147.2	0.54	0.72	0.84	0.97	1.14

Note: A positive value % Daily Load Change indicates the use of less energy for the day.

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Table 7-1 shows the average load reduction per customer based on the program specific assumptions by LCA and weather year conditions and enrollment estimates for 2012. Note that Humboldt is excluded because of its lack of air conditioner load and limited population. As would be expected from a demand resource that is dependent on central air conditioning load, there is significant variation in average impacts across months, regions and weather year conditions. For the service territory as a whole, on a typical event day, the average impact of 0.71 kW based on 1-in-10 year weather conditions is roughly 33% greater than it is based on 1-in-2 year weather conditions (0.54 kW).

Table 7-1
Residential Smart AC Average Customer Load Impacts (kW)
By Weather Year, Local Capacity Area and Day Type
Event Period 2-6 PM, 2012 Enrollment

System Conditions	DAY TYPE	GREATER BAY AREA	GREATER FRESNO	KERN	NORTHERN COAST	SIERRA	STOCKTON	OTHER	ALL
1-in-2	Typical Peak	0.59	0.42	0.42	0.59	0.60	0.59	0.58	0.54
	May Peak	0.07	0.18	0.18	0.04	0.12	0.12	0.12	0.12
	June Peak	0.41	0.28	0.28	0.42	0.38	0.38	0.38	0.36
	July Peak	0.73	0.78	0.79	0.70	0.76	0.76	0.76	0.76
	August Peak	0.64	0.24	0.24	0.67	0.60	0.60	0.58	0.50
	September Peak	0.52	0.34	0.34	0.48	0.56	0.56	0.54	0.47
	October Peak	0.06	0.00	0.00	0.10	0.01	0.01	0.02	0.02
1-in-10	Typical Peak	0.70	0.70	0.70	0.67	0.74	0.74	0.73	0.71
	May Peak	0.37	0.48	0.49	0.33	0.41	0.42	0.42	0.42
	June Peak	0.69	0.60	0.61	0.71	0.65	0.65	0.65	0.65
	July Peak	0.66	0.69	0.69	0.59	0.74	0.74	0.73	0.69
	August Peak	0.72	1.00	1.01	0.66	0.80	0.80	0.80	0.84
	September Peak	0.54	0.48	0.48	0.55	0.52	0.52	0.52	0.51
	October Peak	0.31	0.28	0.28	0.26	0.37	0.36	0.36	0.31

Variation in impacts across LCAs, weather years and day types is driven primarily by differing event period temperatures. This can be seen by comparing tables 7-1 and 7-2. Table 7-2 shows average event period temperature based on the new ex-ante weather data used in this year's analysis. In general, event impacts track temperatures quite closely. Air conditioner load grows substantially starting at around 80 to 85°F. Note that 1-in-2 weather year values are fairly close to 1-in-10 year values in terms of average event period temperatures. Indeed, in some months and LCAs, the 1-in-2 year values are greater than the 1-in-10 year values. This occurs because the monthly system peak days were selected based on system load conditions, and PG&E's territory is quite diverse. Generally, system peaks are driven more so by overnight heat build-up and by conditions in the more populous Bay Area. As a result, it is plausible that PG&E system conditions are more extreme when inland temperatures are not at their highest point.

For example, the July 1-in-2 year temperatures for Fresno and Kern reach 107° F, while the 1-in-10 year values equal 104° F. In other words, for specific area, particularly in the Central Valley, the hottest part of the day during a 1-in-2 year is often similar to the hottest part of the day during a 1-in-10 year.

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Table 7-2
Average Event Period Temperatures
By Weather Year, Local Capacity Area and Day Type
Event Period 2-6 PM, 2012 Enrollment

Weather Conditions	DAY TYPE	GREATER BAY AREA	GREATER FRESNO	KERN	NORTHERN COAST	SIERRA	STOCKTON	OTHER	ALL
1-in-2	Typical Peak	99.5	99.3	99.3	98.8	100.5	100.5	100.3	99.8
	May Peak	86.4	95.4	95.4	83.0	90.9	90.9	90.8	90.8
	June Peak	97.1	96.9	96.9	96.8	97.5	97.5	97.4	97.2
	July Peak	102.2	107.3	107.3	101.4	103.5	103.5	103.6	104.3
	August Peak	100.4	95.1	95.1	100.1	100.6	100.6	100.3	98.7
	September Peak	98.4	98.0	98.0	96.9	100.4	100.3	100.1	98.9
	October Peak	86.9	89.6	89.6	86.8	87.1	87.2	87.3	87.9
1-in-10	Typical Peak	101.3	105.0	105.0	100.7	102.2	102.2	102.3	102.8
	May Peak	95.4	102.4	102.4	94.0	97.4	97.5	97.5	98.4
	June Peak	101.3	104.1	104.1	101.5	101.2	101.2	101.4	102.2
	July Peak	103.0	104.2	104.2	101.8	104.7	104.7	104.5	103.9
	August Peak	101.8	110.4	110.4	100.4	103.8	103.9	104.1	105.3
	September Peak	99.1	101.4	101.4	99.3	99.0	99.0	99.1	99.8
	October Peak	95.2	97.2	97.2	93.5	97.4	97.4	97.2	96.5

Table 7-3 shows the program-specific aggregate load impacts for the SmartAC program for each monthly system peak day and typical event day based on each weather year and all forecast years in which enrollment changes. The program specific impacts on a typical event day grow by roughly 50% between 2010 and 2012.

Table 7-3
Residential SmartAC Aggregate Customer Load Impacts (MW)
By Weather Year, Forecast Year, and Day Type
Event Period 2-6 PM

Weather Year	DAY TYPE	2010	2011	2012-2020
1-in-2	Typical Peak	80.7	109.8	124.4
	May Peak	14.7	23.0	28.6
	June Peak	52.8	71.6	82.5
	July Peak	110.2	153.8	175.7
	August Peak	80.1	104.8	115.0
	September Peak	74.5	100.8	109.8
	October Peak	5.2	5.0	4.8
1-in-10	Typical Peak	104.3	144.9	165.3
	May Peak	55.8	81.0	98.0
	June Peak	94.2	129.5	150.0
	July Peak	99.6	140.2	160.7
	August Peak	123.1	173.6	194.9
	September Peak	81.5	109.8	119.2
	October Peak	49.7	68.2	73.0

The estimates in Table 7-3 also highlight the significance of the criteria used to track progress toward program goals. Based on load impacts for a typical event day based on a 1-in-2 year weather, the aggregate load impact estimated for 2012 would equal about 124 MW. Using 1-in-10 year weather, which is more appropriate for valuing demand resources because it represents the conditions under which the resource is more likely to be called and to provide its greatest value, the 2012 value equals 165 MW. On the system peak day in a 1-in-10 year, the aggregate impact is 195 MW. And, as indicated in Table 7-5, which shows hourly load impacts in 2012, if the hour of system peak is chosen as the most relevant metric, a load reduction of 221 MW could be achieved.

Table 7-4 illustrates how much the aggregate impacts vary across hours within the event window. For example, on the August system peak day based on 1-in-10 year weather conditions, the impact in the third event hour is roughly 40% greater than in the first event hour.

Table 7-5
Residential SmartAC Aggregate Customer Load Impacts (MW)
By Weather Year, Hour and Day Type
Event Period 2-6 PM

System Conditions	DAY TYPE	2:00 to 3:00 PM	3:00 to 4:00 PM	4:00 to 5:00 PM	5:00 to 6:00 PM
1-in-2	Typical Peak Day	92.5	132.8	141.4	130.7
	May Peak Day	25.0	18.9	29.1	41.6
	June Peak Day	55.3	81.4	93.8	99.6
	July Peak Day	133.4	183.5	199.7	186.2
	August Peak Day	89.7	119.6	131.8	118.8
	September Peak Day	79.9	127.7	125.5	105.9
	October Peak	0.0	0.0	7.0	18.9
1-in-10	Typical Peak Day	124.9	175.1	188.8	172.5
	May Peak Day	70.0	93.0	115.2	113.7
	June Peak Day	101.2	156.4	169.1	173.2
	July Peak Day	142.8	179.5	178.0	142.3
	August Peak Day	155.5	210.5	221.3	192.3
	September Peak Day	85.9	125.7	137.7	127.7
	October Peak	49.7	71.6	87.1	83.6

7.2. RECOMMENDATIONS

As discussed above, the load impact analysis underlying the ex ante forecasts was significantly hampered by the human error that led to fact that the M&E sample switches and PCTs were not operated on the planned event days. PG&E is already in the field installing a new end use load research sample and is taking all necessary quality control steps required to ensure that the devices are properly commissioned and controlled as planned in 2010. This new sample will be used for the 2010 load impact evaluation.

As mentioned several times, the Peak Time Rebate proceeding that is currently underway could significantly influence SmartAC enrollment starting in 2011. PG&E's filed tariff that offers a larger PTR incentive to customers who enroll in SmartAC and allow their unit to be operated on PTR event days provides a very strong incentive to enroll. As seen in Section 4 and 5, results from marketing SmartAC to SmartRate customers in 2009, which provides a similar price signal as would PTR, indicate that SmartAC enrollment rates could be quite large once PTR is the default option available to all customers. PG&E should carefully consider implementing a multi-year research effort to understand the potential impact that PTR could have on SmartAC, and vice versa, over the coming years and factor these findings into future evaluations.

8. NON-RESIDENTIAL SMART AC LOAD IMPACT ANALYSIS

This section presents ex ante load impact estimates for the commercial SmartAC program. The estimates are based on average customer impacts developed by FSC and enrollment forecasts developed by the Brattle group. The final analytical output of this section has been provided to PG&E by the Brattle group in the form of impact and enrollment tables for the current year through 2020. This section summarizes that output and provides some detail on how FSC developed impacts to apply to the 2009 commercial SmartAC population.

As discussed in Section 7, the 2009 M&E end use load research sample did not produce load impact estimates for either residential of commercial customers due to a programming error by the PG&E contractor who operates the control devices. As described in Volume 1, Section 6, it was not possible to develop load impact estimates for non-residential SmartAC customers based on the single test event day in 2009. Furthermore, unlike with the residential analysis, which used the 2008 load research sample to estimate ex ante impacts for SmartAC, there was no commercial customer load research sample data for 2008, as there were so few commercial SmartAC participants in 2008. Because of the above constraints, the following approach was developed, making the best use of the available data.

The approach underlying the ex ante estimates provided here relies on reference load estimates based on data from the 2009 commercial M&E end use load research sample (documented in Appendix A) and percentage residential load impact estimates based on the residential load research sample from 2008.[52] Event impacts (as a percent of reference load) were averaged by temperature and by device-type and applied according to temperature and device to commercial sector reference loads calculated using the model documented in Appendix E. Table 8-1 shows the average percent reduction by device type and temperature bin based on the 2008 residential end use load research sample. Based on this sample, PCTs using a 2-1-1 set-back strategy have a higher impact at low temperatures than switches using a 50% cycling strategy. At higher temperatures, this relationship reverses. Note that the 2008 estimation sample did not provide much data in which PCTs were used at times of very high temperature, so PCT effects at the top of the temperature scale should be corroborated with future data. The low temperature values may also be suspect, but are of little consequence as ex ante event days do not occur at such low temperatures.

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[52] See Appendix D for details on the 2008 residential model.

Table 8-1
Event Impacts as Percent of Reference Load by Device Type and Temperature (Estimates from 2008 Residential SmartAC Sample)

Event Average Temperature Range	PCT	Switch
75-80	17	1
80-85	18	7
85-90	19	13
90-95	19	16
95-100	24	28
100-105	23	32
105+	23	35

The load impacts presented here are based on a weighted average by device type of the impacts in Table 8-1. The split between PCTs and switches is quite different for the commercial sector compared with the residential sector. The current split is roughly 72% PCTs and 28% switches, but PG&E is planning to primarily offer PCTs to commercial customers so it is expected that PCTs will be an even larger share of total devices for the commercial sector in the future than it is now. The assumed split underlying the impact estimates presented here is 95% PCTs and 5% switches.

Table 8-2 shows the program specific average load reduction per customer by LCA and weather year. Based on the new ex-ante weather data, days in 1-in-10 years often have approximately the same peak temperatures as those in 1-in-2 weather years (sometimes higher). The major differences between 1-in-10 and 1-in-2 years occur in the early hours of the day, where 1-in-10 morning lows are much higher. The event impacts (on a percentage basis) in this table were applied as a function only of device-type and temperature at each hour. This explains why the 1-in-10 year load impacts during the hottest months are slightly lower than the 1-in-2 year impacts. Impacts in this table also vary on a monthly basis according to the seasonal schedules of businesses in the estimating sample. For example, if a business tends to use more electricity in August than July, independent of the weather, then August impacts for that business can surpass July impacts, even if July is hotter.

Table 8-2
Average Commercial SmartAC Customer Load Impacts (kW) by Weather Year, Local Capacity Area and Day Type (Event Period 2-6 PM, 2012 Enrollment)

Weather Conditions	Day Type	Greater Bay Area	Greater Fresno	Humboldt	Kern	Northern Coast	Other	Sierra	Stockton	All
1-in-2	May Peak	0.92	0.65	0.09	0.70	0.85	0.84	0.80	0.82	0.81
	June Peak	0.96	0.65	0.37	0.68	0.98	0.75	0.77	0.80	0.80
	July Peak	1.07	0.74	0.19	0.77	0.97	0.82	0.88	0.88	0.89
	August Peak	1.10	0.62	0.25	0.70	1.10	0.86	0.87	0.87	0.88
	September Peak	1.06	0.61	0.13	0.66	1.00	0.79	0.81	0.87	0.84
	October Peak	0.82	0.57	0.13	0.62	0.86	0.64	0.67	0.69	0.69
1-in-10	May Peak	0.92	0.65	0.18	0.70	0.90	0.78	0.77	0.74	0.79
	June Peak	0.99	0.67	0.43	0.71	1.02	0.80	0.83	0.79	0.83
	July Peak	0.91	0.60	0.17	0.54	0.93	0.76	0.78	0.74	0.76
	August Peak	0.94	0.63	0.31	0.69	0.90	0.73	0.75	0.74	0.78
	September Peak	1.00	0.68	0.30	0.71	1.04	0.77	0.85	0.80	0.83
	October Peak	0.96	0.65	0.45	0.73	0.97	0.83	0.82	0.78	0.82

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Table 8-3 shows the program-specific aggregate load impacts for the SmartAC program for each monthly system peak day based on each weather year and all forecast years in which enrollment changes substantially. The underlying enrollment estimates were developed by another contractor and are presented in Section 4. The estimates show no program growth in 2010 and 2011, and then a very large increase in 2012 as a result of the influence of default PDP on SmartAC enrollment. Due to the large projected enrollment increase following 2011, aggregate impacts in mid-summer are projected to rise to around 15 MW in 2012 and rise further to 25 MW by 2015.

Table 8-3
Aggregate Commercial SmartAC Load Impacts (MW)
by Forecast Year and Day Type
Event Period 2-6 PM

Weather Year	Day Type	Year		
		2010	2011	2012-2020
1-in-2	May Peak Day	2.05	4.12	5.59
	June Peak Day	2.16	4.30	5.52
	July Peak Day	2.56	5.05	6.14
	August Peak Day	2.68	5.24	6.08
	September Peak Day	2.73	5.27	5.80
	October Peak Day	2.41	4.56	4.78
1-in-10	May Peak Day	1.99	4.01	5.44
	June Peak Day	2.23	4.45	5.73
	July Peak Day	2.17	4.30	5.24
	August Peak Day	2.38	4.64	5.36
	September Peak Day	2.71	5.22	5.74
	October Peak Day	2.83	5.42	5.68

8.1. RECOMMENDATIONS

For the same reasons discussed in Section 7.2, the commercial M&E sample fielded in 2009 did not yield useful data for load impact estimation, although the logger data was very useful for developing reference loads for commercial customers. PG&E is planning to field a new research sample starting in a few weeks, with installation complete by June 1, 2010. As with the residential sample, all necessary steps are being taken to ensure that human error does not thwart the research effort.

As part of its current marketing activity, PG&E is trying several different approaches, including direct mail, direct mail with email follow up, and direct mail with telemarketing follow up. It will be useful to assess the relative effectiveness, and cost-effectiveness, of these various efforts as part of the 2010 ex ante analysis.

APPENDIX A: SUMMARY OF SMARTAC LOAD RESEARCH SAMPLE

As discussed elsewhere, a large end-use research sample was deployed in 2009 to estimate load impacts for SmartAC. While human error on the part of an implementation contractor meant that the data could not be used to estimate load impacts, the sample still proved very useful for estimation of reference loads for ex ante analysis. This appendix briefly describes the sample that was deployed.

The sample consisted of four sub-groups as discussed below.

Residential Participants – 273 residential participants were randomly selected in equal numbers from sampling strata defined by climate zones (R, S and X), control technologies (DLC switch and PCT) and building vintage (buildings built before 1975, between 1975 and 1995 and after 1995). The distribution of participants that were successfully recruited and had loggers installed is summarized in Table A-1.

Table A-1
SmartAC Sample Stratification – 2009 Operating Season

Building Vintage	R			S			X			All		
	Switch	PCT	Total	Switch	PCT	Total	Switch	PCT	Total	Switch	PCT	Total
Pre-1975	14	15	29	12	13	25	13	15	28	39	43	**82**
1975-1995	17	15	32	8	12	20	13	14	27	38	41	**79**
Post 1995	14	12	26	13	15	28	15	15	30	42	42	**84**
Participant Total	**45**	**42**	**87**	**33**	**40**	**73**	**41**	**44**	**85**	**119**	**126**	**245**
Controls			42			40			35			**117**
Total			**129**			**113**			**120**			**285**

Within each stratum formed by the intersection of the stratification variables, residential participants were selected using two-stage cluster sampling. In the first stage, zip codes were randomly selected with probability proportional to the number of participants in each zip code contained within the stratum. In the second stage, three participants were randomly selected from each zip code.

Residential Non-Participants – 120 residential non-participants were also randomly selected in equal numbers (40) from each climate zone. Table A-1 shows the distribution of non-participants that were successfully recruited and had loggers installed. The non-participants were selected from the same zip codes from which residential participants were chosen. The purpose of the residential non-participant sample was to provide a comparison of the daily air conditioner use for SmartAC participants and other customers who have not elected to participate in this program in order to reveal any effects of selection on the load impacts that are obtained from the program.

Non-Residential Participants – 150 non-residential participants were randomly selected in equal numbers from each climate zone. Within each climate zone, the sample was stratified by business type. Table A-2 shows the distribution of the sample that was successfully recruited and had loggers installed. The list of business types reflects the distribution of business types within the current, small participant population that existed at the time.

Table A-2
Non-Residential Participants by Climate Zone and Business Type

Industry	Participants	Non-Participants
Agriculture, Mining & Construction	2	
Manufacturing	2	
Wholesale, Transport & other utilities	4	
Retail stores	19	1
Offices, Hotels, Finance, Services	55	3
Schools	1	
Institutional/Government	31	
Other or unknown	12	62
Total	**126**	**66**

Non-Residential Exploratory Sample –To evaluate the potential load relief obtainable from the non-residential population, loggers were placed on a sample of high potential customers. High potential customers were identified using regression analysis based on hourly data from PG&E's load research sample. The regression analysis separated weather and non-weather sensitive load, and weather sensitive load was then regressed against variables representing location, business type and weather so that potential high load customers can be identified from the general population. Based on this analysis, a sample was chosen from the top quartile of likely high-load customers, stratified by energy use and business type. Table A-2 shows the sample that was recruited.

APPENDIX B: SMART RATE CUSTOMER CHOICE MODEL

Probit Model for Customer Acceptance as a Function of Promotional Features and Demographics

Variable	Estimated Coefficient	Standard Error	Z stat	P>Z	95% Confidence Interval
Lnincent	0.1018284	0.0064291	15.84	0	0.0892276
CS_Brochure	-0.1427135	0.0153545	-9.29	0	-0.1728078
E_Brochure	-0.0475321	0.0152956	-3.11	0.002	-0.077511
F_Brochure	-0.0619102	0.0157965	-3.92	0	-0.0928708
Touch2	-0.09381	0.0144467	-6.49	0	-0.1221251
Touch3	-0.190967	0.018978	-10.06	0	-0.2281632
SAC	0.9947819	0.0210996	47.15	0	0.9534276
CARE	0.190162	0.016675	11.4	0	0.1574797
lnincentxSAC	-0.0020911	0.0109332	-0.19	0.848	-0.0235199
lnincentxCARE	0.0225324	0.003951	5.7	0	0.0147886
SACxCARE	-0.0584702	0.0273411	-2.14	0.032	-0.1120577
lnincentxSACxCARE	-0.0415618	0.0168897	-2.46	0.014	-0.074665
early_summer	-0.1453046	0.0146102	-9.95	0	-0.1739401
late_summer	-0.3987957	0.0133572	-29.86	0	-0.4249753
Sofferxpct_spanish	0.1825791	0.061863	2.95	0.003	0.0613298
M_income	0.0342332	0.0024131	14.19	0	0.0295036
lnincentxmincome	-0.0011046	0.0006396	-1.73	0.084	-0.0023583
pct_spanish	-0.2579063	0.0635495	-4.06	0	-0.382461
Soffer(=0)xpct_spanishxCARE(=1)	0.0421539	0.0658592	0.64	0.522	-0.0869277
Soffer(=1)xpct_spanishxCARE(=1)	0.2522446	0.0391558	6.44	0	0.1755007
CAC_propensity	-1.88115	0.0551625	-34.1	0	-1.989266
CDD65	0.2981035	0.0334384	8.92	0	0.2325655
CACxCDD65	0.1638975	0.0225636	7.26	0	0.1196737
Pct_own	0.1002783	0.030951	3.24	0.001	0.0396154
Urban	0.000972	0.0002153	4.51	0	0.00055
EErebate03-08	0.0700738	0.0098753	7.1	0	0.0507186
EErebate09	0.2212086	0.0140048	15.8	0	0.1937598
Avg_hhsize	-0.0045504	0.0178084	-0.26	0.798	-0.0394541
Region_S	0.4690418	0.0438064	10.71	0	0.3831828
Region_T	0.0525365	0.0993412	0.53	0.597	-0.1421687
Region_X	0.1924318	0.0738016	2.61	0.009	0.0477832
Avg_kwh	-0.0163063	0.0015302	-10.66	0	-0.0193054
Avg_kwhxRegion_T	0.0064281	0.0101386	0.63	0.526	-0.0134432
Avg_kwhxRegion_X	0.0030542	0.0029711	1.03	0.304	-0.002769
M_hvalue	0.1415783	0.0311534	4.54	0	0.0805188
Pct_lt18	0.0950274	0.0744762	1.28	0.202	-0.0509433
Pct_wo_child	0.1051551	0.0785643	1.34	0.181	-0.0488281
V1950-59	0.0649059	0.0185107	3.51	0	0.0286255
V1960-69	0.1481086	0.018921	7.83	0	0.111024
V1970-79	0.2607566	0.0196301	13.28	0	0.2222824
V1980_89	0.3509296	0.0214353	16.37	0	0.3089172
V1990-99	0.4127827	0.0229021	18.02	0	0.3678953
V2000-09	0.4406885	0.0246659	17.87	0	0.3923441
Intercept Term	-2.370464	0.1095601	-21.64	0	-2.585197

APPENDIX C: WEATHER YEAR METHODOLOGY

This appendix contains a memorandum summarizing the methodology that was employed to select the weather data for 1-in-2 and 1-in-10 weather years.

MEMO

Date: December 22, 2009

To: Gil Wong, Pacific Gas & Electric (PG&E)
From: Josh Bode and Zach Mayer, Freeman, Sullivan & Co. (FSC)

Re: 1-in-2 and 1-in-10 Year Weather Update

The load impact protocols require the production of ex-ante load impact estimates under a common set of forecast conditions in order to allow for comparability across programs and for the development of portfolio load impact estimates. The protocols require that ex-ante hourly load impacts be reported based on weather conditions representative of both 1-in-2 and 1-in-10 years for the monthly system peak load day of each month that the program is available. The load impact protocols provide some flexibility in determining the 1-in-2 and 1-in-10 year weather and typical event day characteristics but require an explicit explanation of how they were defined.

Up to the present, PG&E has employed a proxy weather year for the 1-in-2 (2004) and 1-in-10 (2003) weather years. The prior proxy year approach was based on a measure of heat intensity (total summer cooling degree hours) and was not directly linked to system load. More importantly, the monthly conditions underlying load impacts were not aligned with the current practice for allocating capacity value across months and, by connection, cost-effectiveness. Currently, PG&E allocates capacity value based on the relative likelihood that demand exceeds supply, which is primarily driven by a combination of high system load and the likelihood of system failures (e.g. forced generation and transmission outages).

The goal of this task was to develop a methodology that is better aligned with the applications of the load impact estimates – long term planning, resource adequacy, and cost-effectiveness – and produces internally consistent results. The 1-in-10 and 1-in-2 weather year update was constructed using the 90th and 50th percentile peak temperatures for each month of the year, based on an analysis of a sales weighted average temperature representing PG&E's entire service territory.

This memorandum summarizes the analysis conducted to update the 1-in-2 and 1-in-10 monthly system peak hourly weather conditions. A dataset with the 1-in-2 and 1-in-10 hourly weather conditions for each monthly system peak is provided alongside with this memorandum.

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1-in-2 and 1-in-10 Year Weather Selection Process and Results

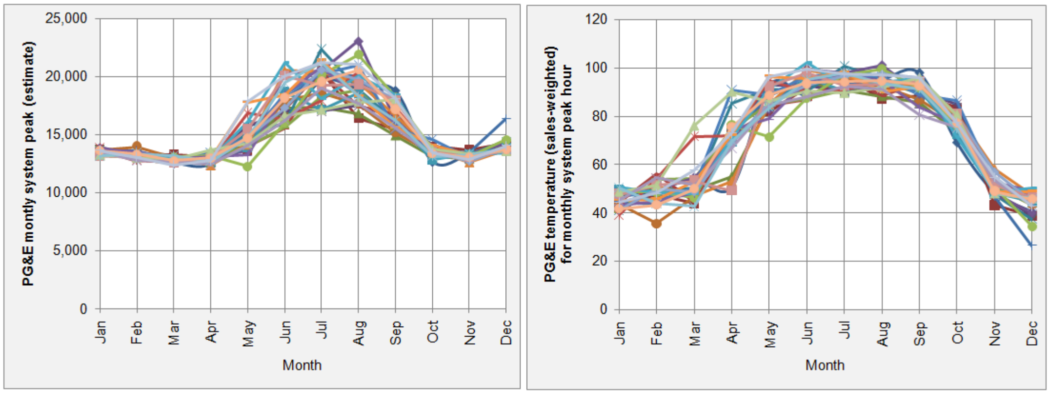
The selection of the 1-in-2 and 1-in-10 monthly system peak weather conditions was based on an analysis of system load data from 2006-2008 and weather from 1983 through 2008 from 25 weather stations located throughout the PG&E territory. The selection of 1-in-2 and 1-in-10 year weather conditions involved the following steps:

- Calculate a PG&E sales-weighted temperature to represent the service territory;
- Estimate system load as a function of weather conditions, hour of day and seasonal factors;
- Predict the system load for 1983-2005 based on historical weather conditions (actual system load was used for 2006-2008);
- Identify the day of the monthly system peak load for each month of each year from 1983-2008;
- Rank the monthly system peak load for each month;
- Identify the 50th and the 90th percentile monthly system peaks (i.e., 1-in-2 and 1-in-10 weather year conditions); and
- Select the weather associated with the selected monthly peaks as the 1-in-2 and 1-in-10 year weather conditions.

System load data from 2006 through 2008 were used to estimate the regression models and to predict system loads for the historical period from 1983-2005 for several reasons. Although it was possible to employ actual system load for 1983-2008, the same weather pattern could produce different system peaks due to changes over the time period in the underlying customer mix, air conditioner saturation, and building stock. The approach estimated what system load would be given current drivers of system load and known historical weather variation. The years of 2006-2008 were selected for estimating the system load regression model because they include a diverse set of weather conditions, enabling the prediction of system load for extreme weather conditions.

Figure 1 shows the distribution of monthly system peak load from the model and associated temperatures for each month of each year for all 25 years.

Figure 1:
Distribution of Estimated (and Actual) Monthly System Peak Loads and Temperatures for 1983- 2008



The figure illustrates three key points. First, the month of the estimated annual system peak varies substantially across years. Second, no single year produces consistently higher loads for all months. As a recent example, the heat wave in July 2006 set the current California system peak load record, yet June, August, and September of 2006 were relatively cool months in comparison with historical weather and system load. Third, small variations in temperature over the summer months drive substantial variation in estimated system load while estimated winter system peak loads show less variation despite a broader range of temperatures.

The 1-in-2 year weather conditions were constructed using hourly data from the 50th percentile system peak day for each month, and the 1-in-10 year weather conditions were constructed using hourly data for the 90th percentile system peak day for each month. The weather data for the entire day, not just the peak hour, was retained. Effectively, the approach selects proxy weather days for the 1-in-2 and 1-in-10 monthly system peaks.

This methodology is superior to using a year's worth of weather data as a proxy for the 1-in-2 and 1-in-10 weather years as it avoids the potential problem of picking a 50th percentile year that has an unusually hot month or picking a 90th percentile year that has an unusually cool month. The 50th and 90th percentile for each month is chosen independently of the other months, which gives a more accurate understanding of expected temperatures associated with "normal" and "extreme" monthly system peak loads for a given month that is not influenced by when heat storms occurred in a particular year.[53] For relatively weather insensitive DR programs, the change in methodology should have little effect on the load impacts. Compared with prior estimates, changes in the estimated available load impact resources are more likely to be seen for highly weather sensitive DR programs such as SmartAC.

Figure 2 compares the 1-in-2 and 1-in-10 year hourly temperature profiles selected for each month of the year. Unlike the proxy year approach, for each month, the 1-in-2 hourly temperature profile is milder than the 1-in-10 hourly temperature profile. However, the driver of system load varies by month. For April through October, system peak loads are driven by

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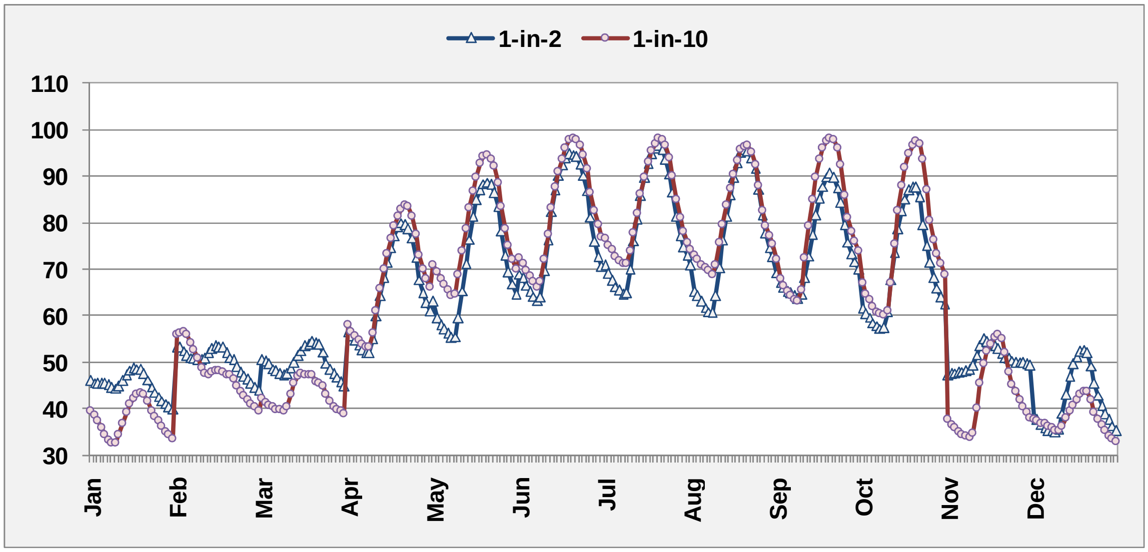
[53] Load impacts are not to be summed across months in a weather year. As a result, the proxy monthly system peak day method does not overstate the severity of weather nor the resources provided by DR, regardless of whether 1-in-2 or 1-in-10 years are employed.

higher temperatures, while for November through March, system peak loads are driven by lower temperatures. The balance of this memorandum discusses the development of the regression model relating system load and weather conditions and summarizes the validity checks conducted to ensure that the regression model accurately predicts system peak.

Figure 2:
Hourly Temperature Profiles for Monthly System Load Peak Days
for 1-in-2 and 1-in-10 Weather Conditions



System Load Regression Model and Validity

The dependent variable in each regression is the natural log of hourly system demand (MW). Because the dependent variable is logged, explanatory variables can be interpreted as the percent change in system load associated with one unit change in the explanatory variables.

The explanatory variables include hourly binary variables to capture the inherent variation in load across hours of the day, day-of-week binary variables to capture variation in usage between week days and weekends and across weekdays, weather variables to capture the influence of temperature on cooling and heating electric loads, and changes in the seasonal pattern of daylight. The model specification was intentionally designed to capture seasonal variation in operating schedules as well as different hourly responses to weather conditions. Lags of prior day system load were not included in the final model because a primary goal was to predict system load for periods when system load lags were outdated. The final model was selected based on sound theory, accuracy on the highest system load days (i.e., lack of bias), explanatory power, and robustness of variables included. Appendix 1 presents the regression parameters.

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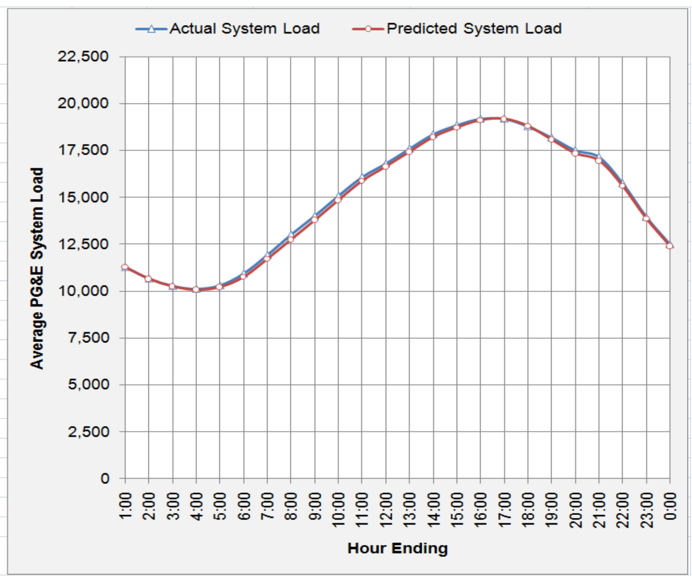
The regressions were estimated using a generalized linear model (GLM) with heteroskedastic and auto-correlation consistent standard errors. The GLM technique was employed with a log link in order to ensure accurate prediction of the log model.[54]

The regression model explained 93.3% of the variation in system load across all hours of the year. Put another way, less than 7% of the variation in system load is explained by variables that are not included in the model.

The most important feature of the regression is the ability to accurately predict system load accurately extreme conditions. Figure 3 compares the actual and regression predicted values for hourly average system load for the top 10 system load days of 2006, 2007, and 2008. The predicted and actual system loads mirror each other closely. Given that the regression is estimated based on all 8760 hours in each year, the model produces relatively accurate estimates of system load under extreme conditions.

Figure 3: Comparison of Actual and Predicted System Load
Average Hourly Profiles of Top 10 System Load Days (2006-2008)

Hour Ending	Actual System Load	Predicted System Load	Mean Error	% Error
1:00	11,285	11,306	21	0.2%
2:00	10,674	10,682	8	0.1%
3:00	10,281	10,276	-5	0.0%
4:00	10,127	10,092	-35	-0.3%
5:00	10,314	10,241	-73	-0.7%
6:00	10,944	10,779	-164	-1.5%
7:00	11,936	11,745	-190	-1.6%
8:00	13,016	12,776	-240	-1.8%
9:00	14,015	13,805	-210	-1.5%
10:00	15,082	14,880	-203	-1.3%
11:00	16,081	15,898	-183	-1.1%
12:00	16,801	16,665	-135	-0.8%
13:00	17,590	17,449	-141	-0.8%
14:00	18,358	18,235	-124	-0.7%
15:00	18,847	18,748	-99	-0.5%
16:00	19,179	19,137	-42	-0.2%
17:00	19,184	19,210	26	0.1%
18:00	18,776	18,829	54	0.3%
19:00	18,179	18,096	-83	-0.5%
20:00	17,508	17,367	-140	-0.8%
21:00	17,150	16,983	-168	-1.0%
22:00	15,747	15,630	-117	-0.7%
23:00	13,958	13,892	-66	-0.5%
0:00	12,497	12,426	-71	-0.6%
Daily Average	**14,902**	**14,803**	**-99**	**-0.7%**



[54] Exponentiation of the predicted log values can produce biased predictions. While there are correction techniques (e,g., Duan's smearing correction) that can be applied to ordinary least square or ARIMA time series models, they assume model errors are normally distrusted. In contrast, GLM models with a log link do not require such corrections, and can also accommodate non-normal dependent variable distributions by allowing for the specification of highly flexible distribution families (e.g. gamma). For additional details on log correction, please refer to Cameron and Trevedi (2005) Microeconometrics: Methods and Applications.

Generalized linear models

Optimization :	ML	No. of obs	49,622.00
		Residual df	49,436.00
		Scale parameter	0.00
Deviance	111.93505	(1/df) Deviance	0.00
Pearson	108.65765	(1/df) Pearson	0.00
Variance function:	V(u) = u^2	[Gamma]	
Link function :	g(u) = ln(u)	[Log]	
HAC kernel (lags):	Newey-West (1)		
Log likelihood =	-510539.21	BIC	-534399.50

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
CDH (Base 65)	0.01266	0.00079	15.95	0.00	0.01110	0.01421
CDH squared	0.00016	0.00003	4.95	0.00	0.00010	0.00023
24 hour lag of CDH	0.00133	0.00024	5.61	0.00	0.00087	0.00180
24 hour lag of CDH - squared	0.00004	0.00001	4.11	0.00	0.00002	0.00006
CDH interactionwith overnight heat intensity	0.00010	0.00000	30.10	0.00	0.00009	0.00010
CDH interaction with overnight heat intensity - squared	0.00000	0.00000	-25.51	0.00	0.00000	0.00000
CDH interaction with weekends	0.00417	0.00040	10.54	0.00	0.00340	0.00495
CDH interaction with weekends - squared	-0.00025	0.00002	-11.90	0.00	-0.00029	-0.00021
CDH interaction with month						
Feb	-0.01504	0.00546	-2.75	0.01	-0.02574	-0.00434
Mar	-0.01693	0.00152	-11.13	0.00	-0.01991	-0.01395
Apr	-0.00640	0.00093	-6.88	0.00	-0.00822	-0.00457
May	-0.00409	0.00058	-7.09	0.00	-0.00522	-0.00296
Jun	-0.00107	0.00051	-2.11	0.04	-0.00206	-0.00008
Jul (base)						
Aug	-0.00071	0.00047	-1.52	0.13	-0.00163	0.00020
Sep	-0.00368	0.00060	-6.16	0.00	-0.00486	-0.00251
Oct	-0.00852	0.00103	-8.26	0.00	-0.01055	-0.00650
Nov	0.00592	0.00239	2.47	0.01	0.00122	0.01061
CDH interaction with month - squared						
Feb	-0.00042	0.00105	-0.40	0.69	-0.00249	0.00164
Mar	0.00059	0.00012	4.77	0.00	0.00035	0.00083
Apr	-0.00014	0.00006	-2.20	0.03	-0.00026	-0.00001
May	0.00005	0.00002	2.06	0.04	0.00000	0.00010
Jun	0.00001	0.00002	0.40	0.69	-0.00004	0.00005
Jul (base)						
Aug	0.00004	0.00002	2.19	0.03	0.00000	0.00008
Sep	0.00009	0.00003	3.48	0.00	0.00004	0.00014
Oct	0.00010	0.00008	1.27	0.20	-0.00005	0.00026
Nov	-0.00177	0.00028	-6.32	0.00	-0.00232	-0.00122
CDH interaction with hour of day						
Hour 1	-0.00478	0.00179	-2.68	0.01	-0.00828	-0.00128
Hour 2	-0.00740	0.00193	-3.84	0.00	-0.01117	-0.00362
Hour 3	-0.01008	0.00209	-4.83	0.00	-0.01417	-0.00599
Hour 4	-0.01096	0.00235	-4.66	0.00	-0.01557	-0.00636
Hour 5	-0.01150	0.00274	-4.19	0.00	-0.01687	-0.00612
Hour 6	-0.00502	0.00419	-1.20	0.23	-0.01322	0.00319
Hour 7	0.00314	0.00550	0.57	0.57	-0.00765	0.01392
Hour 8	-0.00178	0.00346	-0.51	0.61	-0.00856	0.00500
Hour 9	-0.00410	0.00217	-1.89	0.06	-0.00835	0.00016
Hour 10	-0.00539	0.00146	-3.69	0.00	-0.00825	-0.00253
Hour 11	-0.00407	0.00111	-3.66	0.00	-0.00625	-0.00190
Hour 12	-0.00360	0.00095	-3.81	0.00	-0.00545	-0.00175
Hour 13	-0.00296	0.00090	-3.28	0.00	-0.00472	-0.00119
Hour 14	-0.00216	0.00087	-2.48	0.01	-0.00386	-0.00045
Hour 15	-0.00084	0.00076	-1.10	0.27	-0.00232	0.00065
Hour 16 (Base)						
Hour 17	-0.00027	0.00076	-0.36	0.72	-0.00177	0.00122
Hour 18	-0.00088	0.00084	-1.04	0.30	-0.00253	0.00077
Hour 19	0.00031	0.00085	0.37	0.71	-0.00136	0.00199
Hour 20	-0.00068	0.00091	-0.75	0.45	-0.00246	0.00110
Hour 21	0.00171	0.00098	1.75	0.08	-0.00020	0.00362
Hour 22	0.00188	0.00106	1.77	0.08	-0.00020	0.00396
Hour 23	0.00008	0.00112	0.07	0.94	-0.00212	0.00228
Hour 24	-0.00245	0.00123	-1.99	0.05	-0.00486	-0.00004
CDH interaction with hour of day - squared						
Hour 1	-0.00026	0.00015	-1.73	0.08	-0.00056	0.00003

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Hour 2	-0.00015	0.00017	-0.90	0.37	-0.00047	0.00018
Hour 3	0.00001	0.00019	0.06	0.95	-0.00037	0.00039
Hour 4	-0.00002	0.00024	-0.10	0.92	-0.00049	0.00044
Hour 5	-0.00006	0.00030	-0.21	0.84	-0.00066	0.00053
Hour 6	-0.00069	0.00055	-1.25	0.21	-0.00177	0.00039
Hour 7	-0.00156	0.00085	-1.83	0.07	-0.00323	0.00011
Hour 8	-0.00085	0.00045	-1.87	0.06	-0.00173	0.00004
Hour 9	-0.00045	0.00020	-2.26	0.02	-0.00083	-0.00006
Hour 10	-0.00017	0.00010	-1.72	0.09	-0.00036	0.00002
Hour 11	-0.00011	0.00006	-1.93	0.05	-0.00022	0.00000
Hour 12	-0.00004	0.00004	-1.06	0.29	-0.00012	0.00004
Hour 13	-0.00001	0.00003	-0.33	0.74	-0.00008	0.00006
Hour 14	0.00001	0.00003	0.22	0.83	-0.00005	0.00007
Hour 15	0.00000	0.00003	-0.02	0.98	-0.00005	0.00005
Hour 16 (Base)						
Hour 17	0.00002	0.00002	0.64	0.52	-0.00003	0.00006
Hour 18	0.00002	0.00003	0.77	0.44	-0.00003	0.00008
Hour 19	-0.00004	0.00003	-1.45	0.15	-0.00010	0.00001
Hour 20	-0.00007	0.00003	-2.15	0.03	-0.00014	-0.00001
Hour 21	-0.00025	0.00004	-6.03	0.00	-0.00033	-0.00017
Hour 22	-0.00034	0.00005	-6.73	0.00	-0.00044	-0.00024
Hour 23	-0.00032	0.00006	-5.22	0.00	-0.00044	-0.00020
Hour 24	-0.00025	0.00008	-3.19	0.00	-0.00041	-0.00010
HDH (Base 65)	-0.00271	0.00120	-2.26	0.02	-0.00506	-0.00036
HDH squared	0.00034	0.00007	4.50	0.00	0.00019	0.00048
HDH interaction with hour						
Hour 1	-0.00971	0.00129	-7.51	0.00	-0.01225	-0.00718
Hour 2	-0.00841	0.00129	-6.54	0.00	-0.01093	-0.00589
Hour 3	-0.00750	0.00129	-5.83	0.00	-0.01002	-0.00498
Hour 4	-0.00663	0.00129	-5.13	0.00	-0.00916	-0.00410
Hour 5	-0.00521	0.00131	-3.98	0.00	-0.00778	-0.00264
Hour 6	-0.00156	0.00139	-1.12	0.26	-0.00429	0.00117
Hour 7	0.00109	0.00152	0.71	0.48	-0.00190	0.00407
Hour 8	0.00035	0.00142	0.25	0.80	-0.00244	0.00314
Hour 9	-0.00119	0.00136	-0.87	0.38	-0.00386	0.00148
Hour 10	-0.00282	0.00138	-2.04	0.04	-0.00552	-0.00012
Hour 11	-0.00346	0.00143	-2.43	0.02	-0.00625	-0.00066
Hour 12	-0.00248	0.00147	-1.68	0.09	-0.00537	0.00041
Hour 13	-0.00268	0.00157	-1.71	0.09	-0.00575	0.00039
Hour 14	-0.00292	0.00167	-1.75	0.08	-0.00619	0.00035
Hour 15	-0.00211	0.00153	-1.38	0.17	-0.00510	0.00089
Hour 16 (Base)						
Hour 17	0.00546	0.00152	3.58	0.00	0.00247	0.00844
Hour 18	0.00676	0.00163	4.15	0.00	0.00357	0.00994
Hour 19	0.00276	0.00147	1.87	0.06	-0.00013	0.00565
Hour 20	-0.00082	0.00141	-0.58	0.56	-0.00359	0.00194
Hour 21	-0.00559	0.00137	-4.08	0.00	-0.00828	-0.00290
Hour 22	-0.00890	0.00133	-6.68	0.00	-0.01151	-0.00629
Hour 23	-0.01019	0.00129	-7.89	0.00	-0.01272	-0.00766
Hour 24	-0.01004	0.00128	-7.83	0.00	-0.01255	-0.00753
HDH interaction with hour - squared						
Hour 1	0.00011	0.00008	1.50	0.14	-0.00004	0.00026
Hour 2	0.00007	0.00008	0.93	0.35	-0.00008	0.00022
Hour 3	0.00005	0.00008	0.61	0.54	-0.00010	0.00020
Hour 4	0.00002	0.00008	0.29	0.77	-0.00013	0.00017
Hour 5	-0.00001	0.00008	-0.18	0.86	-0.00016	0.00014
Hour 6	-0.00009	0.00008	-1.17	0.24	-0.00024	0.00006
Hour 7	-0.00017	0.00008	-2.09	0.04	-0.00033	-0.00001
Hour 8	-0.00018	0.00008	-2.25	0.02	-0.00033	-0.00002
Hour 9	-0.00014	0.00008	-1.79	0.07	-0.00030	0.00001
Hour 10	-0.00007	0.00008	-0.86	0.39	-0.00023	0.00009
Hour 11	-0.00001	0.00009	-0.17	0.87	-0.00018	0.00015
Hour 12	-0.00001	0.00009	-0.16	0.87	-0.00019	0.00016
Hour 13	0.00004	0.00010	0.40	0.69	-0.00015	0.00023
Hour 14	0.00009	0.00011	0.87	0.39	-0.00012	0.00030
Hour 15	0.00009	0.00010	0.89	0.38	-0.00010	0.00028
Hour 16 (Base)						
Hour 17	-0.00021	0.00009	-2.29	0.02	-0.00040	-0.00003
Hour 18	-0.00029	0.00009	-3.11	0.00	-0.00047	-0.00011
Hour 19	-0.00017	0.00009	-1.96	0.05	-0.00033	0.00000
Hour 20	-0.00007	0.00008	-0.80	0.42	-0.00023	0.00010
Hour 21	0.00008	0.00008	0.94	0.35	-0.00008	0.00023
Hour 22	0.00015	0.00008	1.94	0.05	0.00000	0.00031

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Hour 23	0.00016	0.00008	2.12	0.03	0.00001	0.00032
Hour 24	0.00013	0.00008	1.75	0.08	-0.00002	0.00028
Hour of day effects						
Hour 1	-0.08814	0.00603	-14.61	0.00	-0.09996	-0.07631
Hour 2	-0.13437	0.00617	-21.77	0.00	-0.14647	-0.12227
Hour 3	-0.16282	0.00638	-25.52	0.00	-0.17532	-0.15032
Hour 4	-0.17785	0.00657	-27.05	0.00	-0.19073	-0.16496
Hour 5	-0.17983	0.00681	-26.41	0.00	-0.19317	-0.16649
Hour 6	-0.18483	0.00755	-24.49	0.00	-0.19962	-0.17004
Hour 7	-0.15562	0.00879	-17.70	0.00	-0.17286	-0.13839
Hour 8	-0.08391	0.00815	-10.30	0.00	-0.09988	-0.06794
Hour 9	-0.01114	0.00623	-1.79	0.07	-0.02334	0.00106
Hour 10	0.03482	0.00602	5.78	0.00	0.02302	0.04663
Hour 11	0.04664	0.00603	7.74	0.00	0.03483	0.05845
Hour 12	0.04072	0.00602	6.76	0.00	0.02892	0.05253
Hour 13	0.02913	0.00619	4.71	0.00	0.01700	0.04125
Hour 14	0.01582	0.00642	2.47	0.01	0.00324	0.02839
Hour 15	0.00272	0.00590	0.46	0.65	-0.00885	0.01429
Hour 16 (Base)						
Hour 17	0.07344	0.00886	8.29	0.00	0.05607	0.09082
Hour 18	0.14221	0.00831	17.11	0.00	0.12592	0.15850
Hour 19	0.16150	0.00689	23.45	0.00	0.14800	0.17499
Hour 20	0.16923	0.00628	26.96	0.00	0.15693	0.18154
Hour 21	0.16596	0.00592	28.05	0.00	0.15437	0.17756
Hour 22	0.11791	0.00583	20.24	0.00	0.10649	0.12933
Hour 23	0.03144	0.00573	5.49	0.00	0.02021	0.04267
Hour 24	-0.05545	0.00583	-9.50	0.00	-0.06688	-0.04401
Weekend day effect	0.11418	0.00382	29.85	0.00	0.10669	0.12168
Weekend hour of day effects						
Hour 1	-0.09762	0.00436	-22.38	0.00	-0.10617	-0.08908
Hour 2	-0.09218	0.00437	-21.11	0.00	-0.10074	-0.08362
Hour 3	-0.08705	0.00439	-19.83	0.00	-0.09565	-0.07845
Hour 4	-0.07579	0.00440	-17.21	0.00	-0.08442	-0.06716
Hour 5	-0.04583	0.00445	-10.30	0.00	-0.05454	-0.03711
Hour 6	0.01356	0.00472	2.87	0.00	0.00431	0.02281
Hour 7	0.08465	0.00501	16.91	0.00	0.07484	0.09446
Hour 8	0.07941	0.00484	16.42	0.00	0.06993	0.08889
Hour 9	0.05061	0.00467	10.85	0.00	0.04147	0.05975
Hour 10	0.03359	0.00459	7.32	0.00	0.02459	0.04259
Hour 11	0.02505	0.00462	5.42	0.00	0.01600	0.03411
Hour 12	0.01302	0.00471	2.76	0.01	0.00377	0.02226
Hour 13	0.01113	0.00484	2.30	0.02	0.00164	0.02062
Hour 14	0.01289	0.00502	2.57	0.01	0.00304	0.02274
Hour 15	0.00726	0.00474	1.53	0.13	-0.00202	0.01654
Hour 16 (Base)						
Hour 17	-0.01798	0.00504	-3.57	0.00	-0.02786	-0.00810
Hour 18	-0.04093	0.00543	-7.54	0.00	-0.05157	-0.03029
Hour 19	-0.05129	0.00509	-10.07	0.00	-0.06127	-0.04131
Hour 20	-0.05912	0.00483	-12.24	0.00	-0.06858	-0.04965
Hour 21	-0.06534	0.00459	-14.22	0.00	-0.07434	-0.05633
Hour 22	-0.06313	0.00453	-13.93	0.00	-0.07202	-0.05425
Hour 23	-0.06347	0.00445	-14.28	0.00	-0.07219	-0.05476
Hour 24	-0.06453	0.00444	-14.54	0.00	-0.07323	-0.05583
Daylight effects (for hours with variation)						
Hour 6-7 x daylight	-0.03051	0.00400	-7.64	0.00	-0.03834	-0.02268
Hour 7-8 x daylight	-0.00701	0.00381	-1.84	0.07	-0.01448	0.00047
Hour 16-17 x daylight	-0.05163	0.00655	-7.89	0.00	-0.06446	-0.03880
Hour 17-18 x daylight	-0.08856	0.00504	-17.56	0.00	-0.09844	-0.07868
Hour 18-19 x daylight	-0.09166	0.00393	-23.34	0.00	-0.09936	-0.08396
Hour 19-20 x daylight	-0.05982	0.00340	-17.58	0.00	-0.06649	-0.05315
Hour 20-21 x daylight	-0.02102	0.00419	-5.01	0.00	-0.02924	-0.01280
Month effects						
Jan	-0.05501	0.00270	-20.41	0.00	-0.06029	-0.04972
Feb	-0.06439	0.00261	-24.69	0.00	-0.06950	-0.05928
Mar	-0.06325	0.00250	-25.31	0.00	-0.06814	-0.05835
Apr	-0.05617	0.00242	-23.25	0.00	-0.06090	-0.05143
May	-0.04495	0.00222	-20.25	0.00	-0.04930	-0.04060
Jun	-0.01789	0.00199	-8.97	0.00	-0.02180	-0.01398
Jul (base)						
Aug	0.00382	0.00198	1.93	0.05	-0.00006	0.00770
Sep	-0.02452	0.00213	-11.52	0.00	-0.02869	-0.02034
Oct	-0.06294	0.00224	-28.12	0.00	-0.06733	-0.05855
Nov	-0.06337	0.00260	-24.36	0.00	-0.06847	-0.05828

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Dec	-0.03867	0.00283	-13.66	0.00	-0.04422	-0.03312
Constant	9.23160	0.00516	1788.83	0.00	9.22148	9.24171

APPENDIX D: SUMMARY OF RESIDENTIAL SMARTAC EX ANTE MODEL DEVELOPMENT

As discussed in Section 7, due to a programming error by a PG&E contractor who operates the SmartAC load control devices, it was not possible to estimate load impacts using the 2009 M&E end use load research sample. Instead, the ex ante estimates are based on the 2008 load research sample. This appendix documents the modeling and analysis that was done using the 2008 data.

Air-conditioning energy use was analyzed using regression methods to isolate the effect of the 19 2008 SmartAC events. The final model uses various weather variables interacted with times of day, days of the week and months of the year to capture regularities in customer AC use. The model also uses a combination of weather variables and time variables to specify event effects and post-event effects, in order to capture the regularities in effect across hours of the day and hours of the event.

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 customer in the sample, but using a common regression model in each case. For all customers, factors used to estimate AC energy usage included two basic types of variables:

- Weather variables interacted with time indicators. These allow the model to take into account different customer reactions to weather conditions at different times of day, times of the week and times of year. For example, a residential customer's AC usage might respond strongly to high temperatures on a Saturday afternoon when he/she is at home, while it might not respond at all on a Wednesday afternoon when he/she is at work;
- Weather variables interacted with event-specific variables, such as hour of the event or setback strategy (ramp versus cycle for thermostats). These variables allow the model to take advantage of regularities across events. In turn, this allows the model to better predict reference load on event days.

The final regression model of AC usage for residential customers is quite rich in that it allows for many different types of temperature-based effects at different times. Standard linear regression was applied to obtain coefficients. Standard errors were calculated using the Newey-West method, which allows for both heteroskedasticity and correlation in the error term over time. The model for a given individual customer is:

$$Load_t = a + \sum_{w=1}^{2}\sum_{h=1}^{24} b_{wh} * I_w * I_h * CDH_t + \sum_{w=1}^{2}\sum_{h=1}^{24} c_{wh} * I_w * I_h * (CDH_t)^2$$

$$+ \sum_{w=1}^{2}\sum_{h=1}^{24} d_{wh} * I_w * I_h * CDH_t * nightCDH_t + \sum_{w=1}^{2}\sum_{h=1}^{24} e_{wh} * I_w * I_h * CDD_t$$

$$+ \sum_{h=12}^{19} f_h I_h * CDH_t * event + \sum_{h=12}^{19} g_h I_h * (CDH_t * event)^2 + \sum_{e=1}^{6} i_e I_e * CDH_t * event$$

$$+ \sum_{e=1}^{6} j_e I_e * (CDH_t * event)^2 + + \sum_{e=1}^{6} k_e I_e * CDH_t * event * ramp$$

$$+ \sum_{e=1}^{6} m_e I_e * (CDH_t * event * ramp)^2 + \sum_{p=1}^{8} n_p I_p * eventCDH + \sum_{p=1}^{8} p_p I_p * eventCDH^2$$

The subscript *t* indicates time. Table D-1 defines the variables and describes the effects they seek to identify.

Table D-1: Description of AC Load Regression Variables

Variable	Description
Load	Average hourly air conditioning load
a	*a* is an estimated constant
b-p	*b-p* are estimated parameters (*l* and *o* are excluded for clarity)
I_m	Dummy variables for month of the year, designed to pick up seasonal effects
I_d	Dummy variables for day type, designed to pick up day of the week effects
I_w	Dummy variables designed to pick up weekend versus weekday effects
I_h	Dummy variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior
I_e	Dummy variables representing the hours of the event, designed to estimate the changing effect of the event as it progresses
I_p	Dummy variables representing the hours of the post-event period, designed to estimate the snap-back effect and its dissipation over time
CDH	Cooling degree hours (defined as the maximum of 0 or temperature–base temperature) which is correlated with cooling load. Base temperature is chosen based on the best fitting base for each customer
CDH^2	The square of CDH, designed to identify nonlinearities in the relationship between temperature and usage behavior
CDD	Cooling degree days (defined as the maximum of zero and the average of the minimum and maximum daily temperature) which is correlated with cooling load and which identifies the effect of prolonged heat versus short term heat. Base temperature for CDD is 70 degrees Fahrenheit.
event	An indicator variable for any time during an event
ramp	An indicator variable for anytime during an event that a 2-1-1 ramp strategy is employed for PCTs
nightCDH	The sum of CDH from midnight to six am on a given day which identifies the effect of high overnight temperatures on energy usage the next day
eventCDH	The sum of CDH during an event, designed to model the potentially larger snap-back effect due to a hotter event

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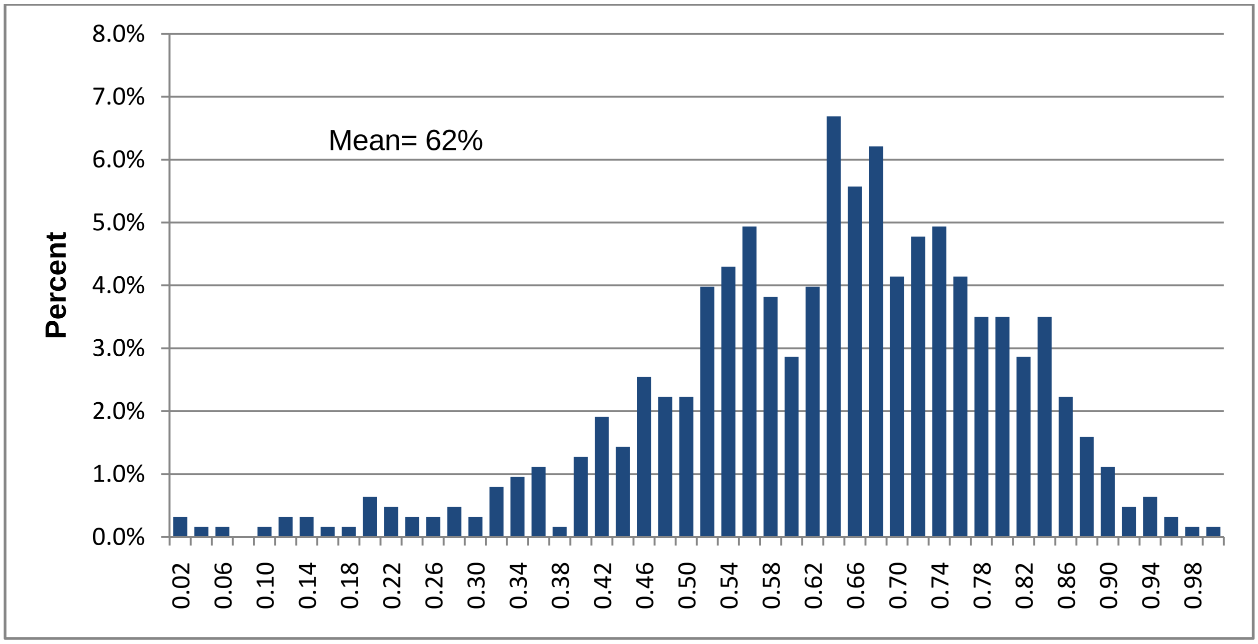
Goodness of Fit Measures

Figure D-1 shows the distribution of R-squared values from the individual residential customer regressions. The average R-squared among the residential customer regressions is 62%. Values range from close to zero to close to 1. Approximately 80% of the regressions have R-squared values above 50%. This means that even at an individual level, the model explains over half of the variation in load for the bulk of the population.

Figure D-1
Distribution of R-squared Values from Individual Regressions, Residential Customers



While the individual customer regressions do a reasonably good job of explaining the variation in electricity use for both residential and commercial customers, in aggregate, nearly all of the variation in energy use across hours is explained by the model specification. When the predicted and actual values are aggregated across the individual results, the model explains 98% of the variation in AC energy use. Put another way, only about 2% of the variation in energy use over time is explained by variables that are not included in the model. In order to estimate the average customer R-squared values, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The same process was performed to estimate the amount of explained variation for the average customer in specific segments. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:

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$$\mathbf{R^2} = 1 - \frac{\sum_t (\hat{y}_t - y_t)^2}{\sum_t (\hat{y}_t - \bar{y})^2}$$

Where:

y_t is the actual energy use at time t

$\hat{y}_t$ is the regression predicted energy use at time t

$\bar{y}$ is the actual mean energy use across all time periods.

Table D-2 summarizes the amount of variation explained by the regression model for the average customer by device type and by local capacity area. All values are over 80%, and most are over 90%.

Table D-2
R^2 of aggregate load, 2008 SmartAC Residential Load Research Sample
By Device Type and Local Capacity Area

LCA	PCT	Switch	Total
Greater Bay Area	94%	95%	96%
Greater Fresno	98%	97%	98%
Other	88%	87%	91%
Stockton	95%	94%	95%
Total	97%	97%	98%

Model Accuracy and Validity Assessment

The most important feature of load impact analysis is the ability to predict accurately customer load and load reductions under the extreme conditions for which demand response is designed to provide a reliable resource. The accuracy of load impact estimates depends directly on the ability of the model to predict load during event periods. To assess the accuracy and validity of the model, we compared actual and predicted average load values across hour and temperature. These diagnostics reinforce the evidence that the impact estimates are accurate.

Figure D-2 shows the actual average hourly energy use of residential customers on non-event days compared to the regression predicted average customer energy use. Figure D-3 shows the same thing for event days, and also includes average hourly reference load. In each case, the close match between predicted values and actual values reflects the ability of the regressions to predict accurately overall. It is particularly reassuring that the predicted and actual loads match up so well across the hours of the event days. This is strong corroboration that estimated event impacts are accurate.

Figure D-2
Average Actual and Predicted AC Load for Non-Event Days

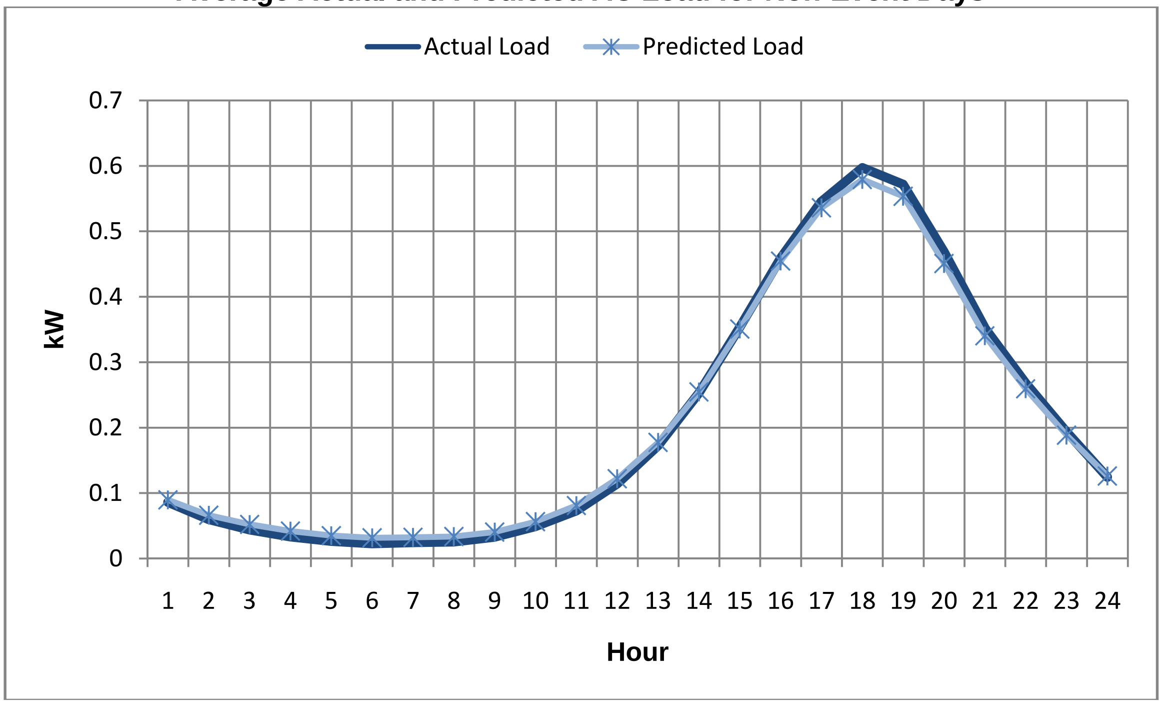
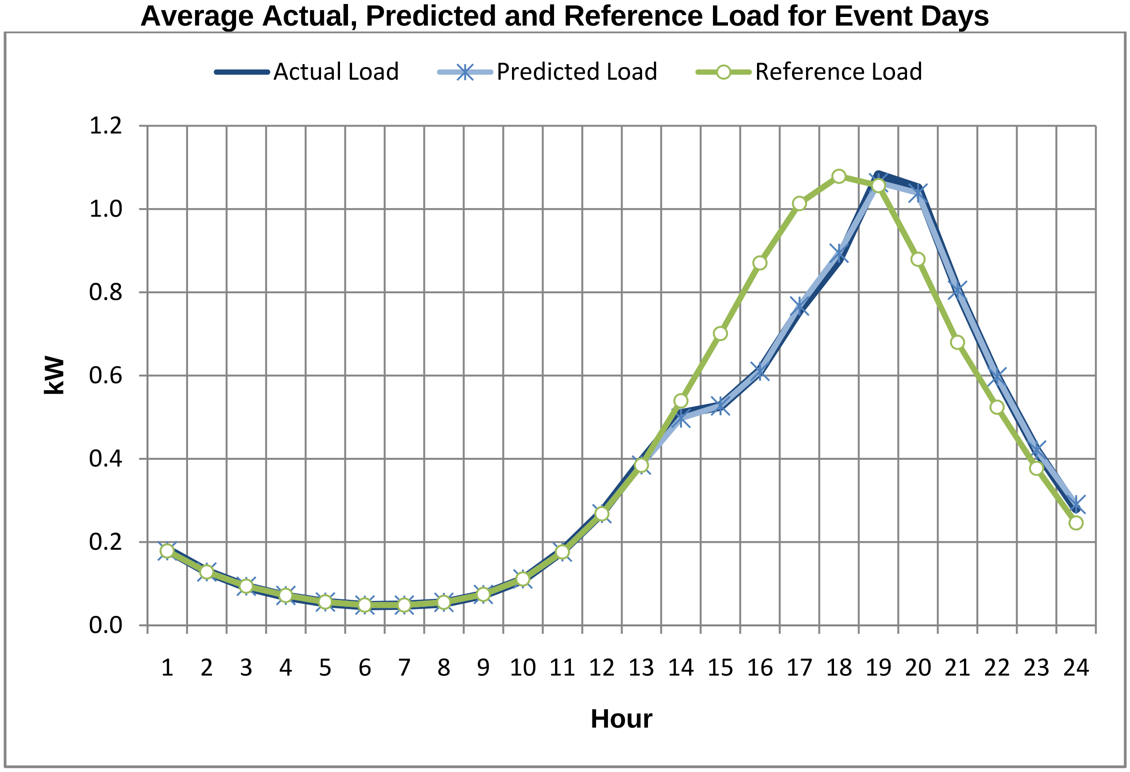


Figure D-3
Average Actual, Predicted and Reference Load for Event Days



In addition to accuracy across hours of the day, accurately estimated impacts require predicted loads to be accurate across different temperature conditions. Figures D-4 and D-5 show that the predicted loads match the actual loads quite well across a wide range of temperatures on both event days and non-event days. On the event day, reference loads naturally deviate from actual loads at high temperatures due to the event itself.

Figure D-4
Average Residential Customer Actual and Predicted Values for Non-Event Days

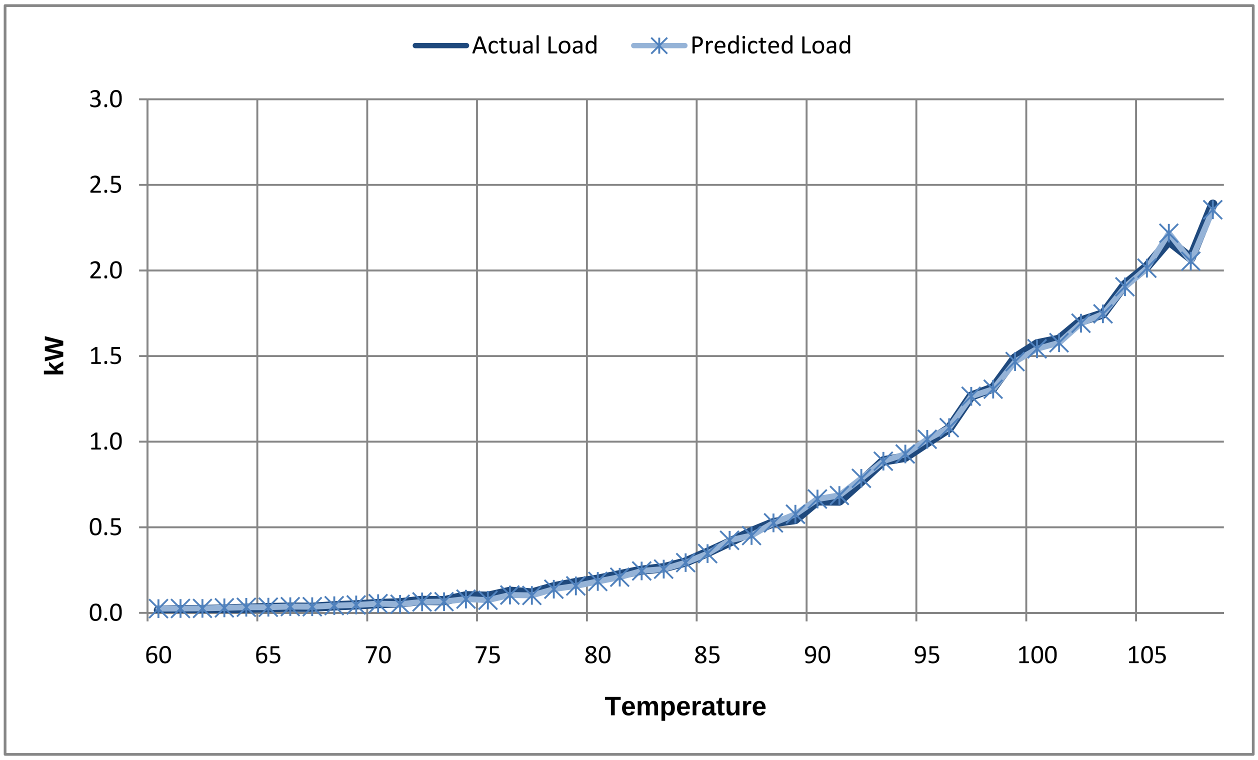
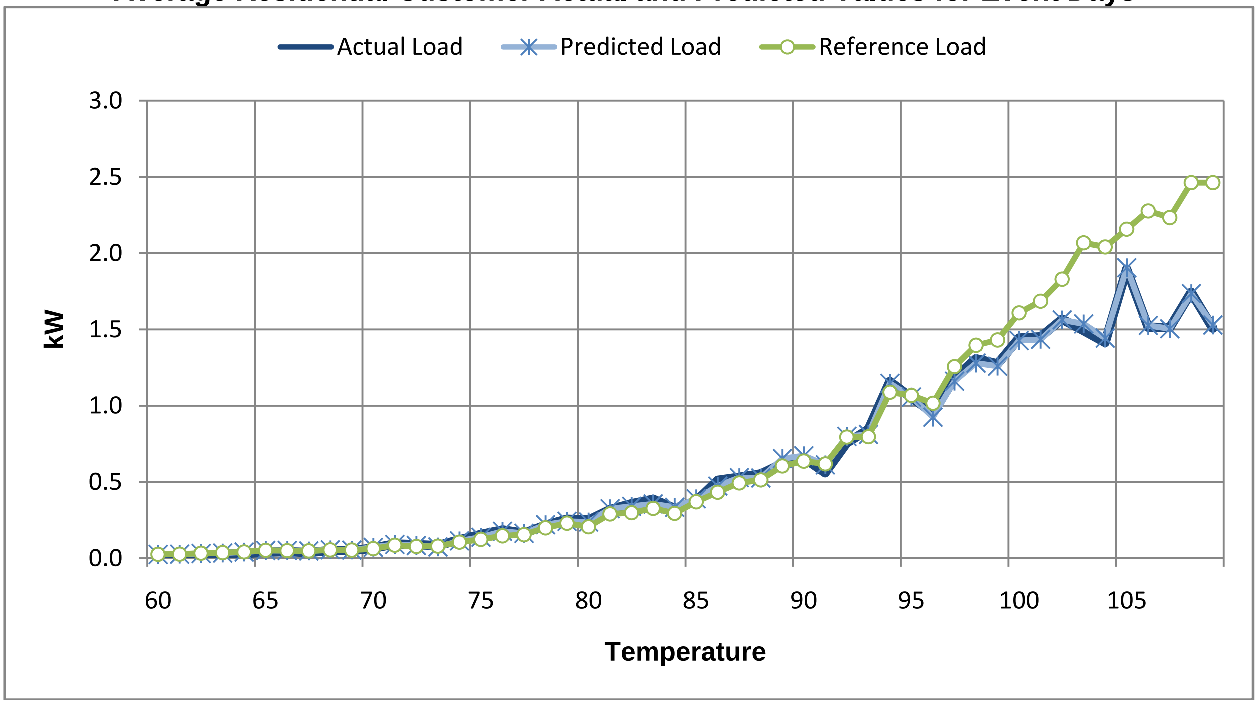


Figure D-5
Average Residential Customer Actual and Predicted Values for Event Days



Similar comparisons of actual and predicted values were conducted by month, day of week, individual days, and various other iterations – all of which indicated that the results were not only unbiased for the average day and average customer, but also unbiased across multiple customer segments and temporal characteristics.

APPENDIX E: SUMMARY OF NON-RESIDENTIAL SMARTAC REFERENCE LOAD MODEL ESTIMATION

AC energy use for the SmartAC 2009 Commercial load research sample was analyzed using regression methods to model load at different times of day and during different weather conditions. 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 customer in the sample, but using a common regression model in each case. For all customers, factors used to estimate AC usage patterns included two basic types of variables:

- Indicator variables that equal one at particular times; for example, between one and two pm on weekdays. These allow the model to account for different average customer usage at various times of day, times of the week and times of year;
- Weather variables interacted with time indicators. These allow the model to take into account different customer 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 he/she is at home, while it might not respond at all on a Wednesday afternoon when he/she is at work;

The final regression model of whole-building usage for residential and commercial customers is quite rich in that it allows for many different types of time-based and temperature-based effects. Standard linear regression was applied to obtain coefficients. Standard errors were calculated using the Newey-West method, which allows for both heteroskedasticity and correlation in error over time. The model for a given individual customer is:

$$Usage_t = a + \sum_{m=5}^{9}\sum_{h=1}^{24} c_{mh} * I_m * I_h + \sum_{d=1}^{5}\sum_{h=1}^{24} d_{dh} * I_d * I_h + \sum_{w=1}^{2}\sum_{h=1}^{24} e_{wh} * I_w * I_h * CDH_t$$
$$+ \sum_{w=1}^{2}\sum_{h=1}^{24} f_{wh} * I_w * I_h * (CDH_t)^2 + \sum_{h=1}^{24} g_h * I_h * CDD_t + U_t$$

The subscript *t* indicates time. Table E-1 defines the variables and describes the effects they seek to identify.

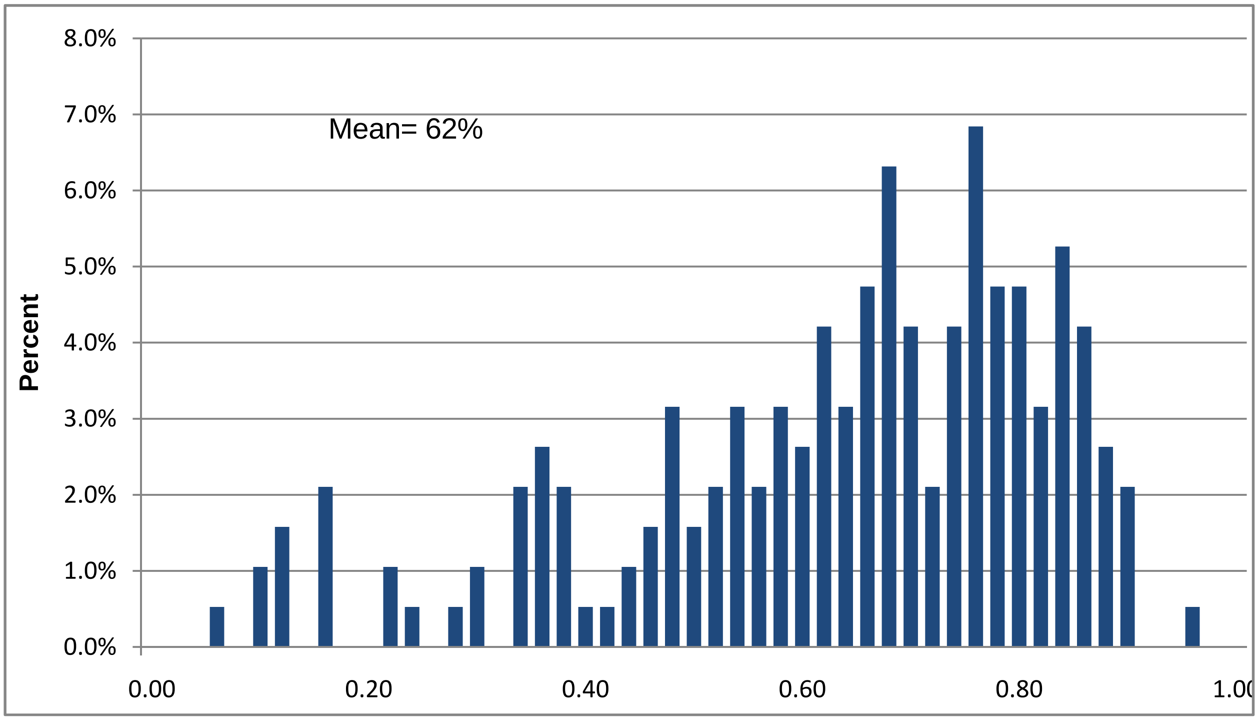
Table E-1
Description of Commercial AC Regression Variables

Variable	Description
a	a is an estimated constant
c-g	b-g are estimated parameters
rh	Relative humidity which is correlated with AC usage behavior
I_m	Dummy variables for month of the year, designed to pick up seasonal effects
I_d	Dummy variables for day type, designed to pick up day of the week effects
I_w	Dummy variables designed to pick up weekend versus weekday effects
I_h	Dummy variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior
CDH	Cooling degree hours (defined as the maximum of 0 or temperature – base temperature) which is correlated with cooling load. Base temperature is chosen based on the best fitting base for each customer
CDH^2	The square of CDH, designed to identify nonlinearities in the relationship between temperature and usage behavior
CDD	Cooling degree days (defined as the maximum of zero and the difference between the average daily temperature and 70 degrees) which is correlated with cooling load and which identifies the effect of prolonged heat versus short term heat.
U	The error term

Goodness of Fit Measures

Figure E-1 shows the distribution of R-squared values from the individual residential customer regressions. The average R-squared among the residential customer regressions is 62%. Values range from close to zero to close to 1. Over 75% of the regressions have R-squared values above 50%. This means that even at an individual level, the model explains over half of the variation in load for the bulk of the population.

Figure E-1
Distribution of R-squared Values from Individual Regressions, Commercial Customers



While the individual customer regressions do a reasonably good job of explaining the variation in electricity use, in aggregate, nearly all of the variation in energy use across hours is explained by the model specification. When the predicted and actual values are aggregated across the individual results, the model explains 96% of the variation in AC energy use. Put another way, only about 4% of the variation in energy use over time is explained by variables that are not included in the model. In order to estimate the average customer R-squared values, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The same process was performed to estimate the amount of explained variation for the average customer in specific segments. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:

$$\mathbf{R^2 =} \; 1-\frac{\sum_t (\hat{y}_t - y_t)^2}{\sum_t (\hat{y}_t - \bar{y})^2}$$

Where:

y_t is the actual energy use at time t

$\hat{y}_t$ is the regression predicted energy use at time t

$\bar{y}$ is the actual mean energy use across all time periods.

Table E-2 summarizes the amount of variation explained by the regression model for the average customer by device type and by local capacity area. Values are quite high, with the lowest at 75% in the Northern Coast area.

Table E-2
R^2 of Aggregate Load, 2009 SmartAC Commercial Load Research Samples by Device Type and Local Capacity Area

LCA	PCT	Switch	Total
Greater Bay Area	93%	87%	93%
Greater Fresno	95%	94%	95%
Kern	84%		84%
Northern Coast	75%		75%
Other	91%	86%	91%
Sierra	88%	90%	91%
Stockton	91%	91%	92%
Total	95%	94%	96%

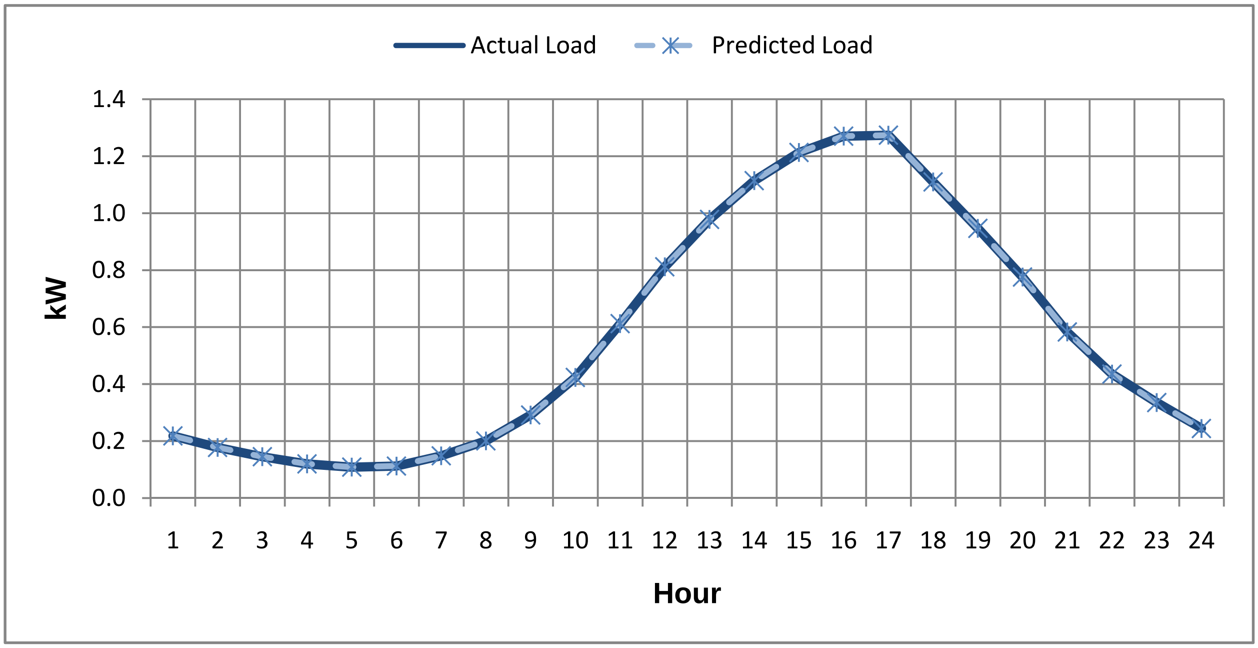
Model Accuracy and Validity Assessment

The most important feature of load impact analysis is the ability to predict accurately customer load and load reductions under the extreme conditions for which demand response is designed to provide a reliable resource. The accuracy of load impact estimates depends directly on the ability of the model to predict load during event periods. In the 2009 Commercial SmartAC load research sample there are no actual events to measure,[55] but we can assess the model's accuracy for reference load. To assess the accuracy and validity of the model, we compared actual and predicted average load values across hour and temperature. These diagnostics reinforce the evidence that the impact estimates are accurate.

Figure E-2 shows the actual average hourly AC use of commercial customers compared to the regression predicted average customer AC use. The extremely close match between predicted values and actual values reflects the ability of the regressions to predict accurately overall. This is strong corroboration that estimated reference loads are accurate.

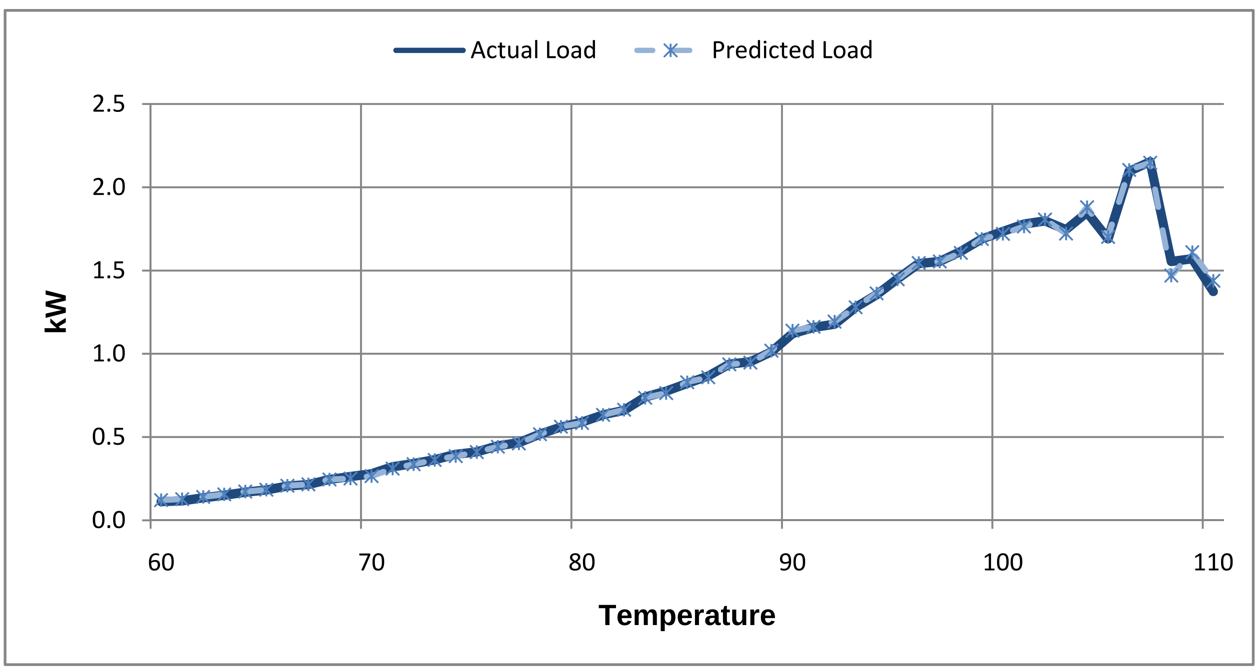
[55] See the section we discuss this in.

Figure E-2
Average Actual and Predicted AC Load by Hour of the Day



In addition to accuracy across hours of the day, reference loads should be accurate across different temperature conditions. Figure E-3 shows that the reference load matches the actual load quite well across a wide range of temperatures.

Figure E-3
Average Commercial Customer Actual and Predicted Values by Temperature



Similar comparisons of actual and predicted values were conducted by month, day of week, individual days, and various other iterations – all of which indicated that the results were not only unbiased for the average day and average customer, but also unbiased across multiple customer segments and temporal characteristics.