FREEMAN, SULLIVAN & CO.

A MEMBER OF THE FSC GROUP

2009 Load Impact Evaluation of San Diego Gas & Electric Company's Summer Saver Program

Final Report

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Freeman, Sullivan & Co.
101 Montgomery St., 15th Floor
San Francisco, CA 94104

Prepared for:
San Diego Gas & Electric Co.

Prepared by:
Stephen S. George, Ph.D.
Josh Bode, M.P.P.
Josh Schellenberg, M.A.
Seth Morgan, M.A.
Freeman, Sullivan & Co.

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1. EXECUTIVE SUMMARY

San Diego Gas and Electric Company's (SDG&E) Summer Saver program is a demand response resource based on air conditioning load control. It is implemented through an agreement between SDG&E and Alternate Energy Resources, formerly known as Comverge, and is currently scheduled to continue through 2016. This report provides ex post load impact estimates for the Summer Saver program for 2009 and ex ante load impact forecasts for 2010 through 2020.

The Summer Saver program is available to residential customers and commercial facilities that use up to a maximum of 100kW on average during a 12-month period. The Summer Saver season runs from May 1st through October 31st and does not notify participating customers of an event. A Summer Saver event may be triggered the day of an event if warranted by temperature and system load conditions.

There are a variety of enrollment options for both residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time, and can have cycling occur only on weekdays or on weekends as well. Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive paid for each option varies and is based on the number of air conditioning tons being controlled at each site.

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

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

1.1. Ex Post Load Impact Estimates

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

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

MW. The impacts ranged from a low of 17.4 MW on July 21st to a high of 27.7 MW on August 27th. The percent load reduction also varied across events, from a low of 35% on July 21st to a high of 46% on August 28th.

Residential customers accounted for almost two thirds of the enrolled tonnage of air conditioning and almost three quarters of the total load reduction. The average load reduction for residential and commercial customers is quite similar, 0.18 kW/ton and 0.14 kW/ton, respectively. The percent load reduction is much higher for residential customers compared with commercial customers, due in large part to the different cycling options offered to the two segments. Residential customers are split about 50/50 between 50% and 100% cycling, while commercial customers are split 60/40 between 50% and 20% cycling.

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

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

Table 1-2
2009 Average Hourly Load Reduction for Event Period by Event Day
All Commercial Summer Saver Customers, kW per Ton

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

Table 1-3
2009 Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Customers, kW per Ton

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

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

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

An analysis of high and low responders showed that roughly 25% of both residential and commercial customers provided little or no response across the seven events in 2009. On the other hand, about 10% of residential and commercial participants provided average load reductions exceeding 0.5 kW/ton. Regression analysis of the drivers of high response among residential customers indicated that customers with a high correlation between monthly kWh and cooling degree hours, a proxy for high air conditioning load, were much more likely to be high responders. This result is not surprising, but the magnitude and high statistical significance of the variable is important. This is a variable that can be calculated for all residential customers from existing information and, as such, one that could be used to target high responders as part of future marketing efforts.

An analysis of the distribution of commercial impacts indicated that customers in the Religious Institutions and Restaurant segments were much less likely to be high responders. Customers in other segments, especially Retail Stores, were more likely to be high responders. Readily available North American Industry Classification System (NAICS) codes can be used to determine business type and, as such, could be used to target high responders and avoid low responders as part of future marketing efforts.

The analysis summarized above and presented throughout most of this report was based on end-use interval data. An analysis was done comparing load impact estimates for residential and commercial Summer Saver participants based on regression modeling using whole building interval data and end-use interval data. The load impact estimates using the two sets of data were almost indistinguishable for the residential participant population as a whole and for the residential 100% cycling group. For the residential 50% cycling group, there were more noticeable differences on average across the seven events, and the estimates based on whole building data were about 6% lower than those based on end use interval data. These findings indicate that, once smart meters are widely deployed among the residential participant population, SDG&E will be able to confidently base residential load impact evaluations on whole building data rather than the more expensive end use load research data.

The comparison of whole building and end use data for commercial Summer Saver participants was not as conclusive. There was a systematic, downward bias in the estimates based on commercial whole building data compared with those based on end use data. The average impact across the seven event days based on the whole building data analysis was approximately 15% lower than the average impact estimate based on the end use data. For future evaluations we recommend that SDG&E continue to explore whether commercial load impact estimates based on whole building data can be confidently used as opposed to using end use data loggers.

1.2. Ex Ante Load Impact Estimates

Tables 1-4 through 1-6 contain estimates of ex ante load impacts for the typical event day and each monthly system peak day under 1-in-2 and 1-in-10 year weather conditions for residential participants, commercial participants and the program as a whole, respectively. These are based on projected enrollment in the steady state year, 2012. For a typical event day and 1-in-2 year weather conditions, aggregate impacts equal 22.8 MW. The estimate for a typical event day under 1-in-10 year conditions is 19% higher. On the highest peak day for 1-in-2 year weather conditions, the load reduction is estimated to equal 28.8 MW. With the more extreme 1-in-10 year conditions, the estimated impact is 31.9 MW.

Table 1-4
Average and Aggregate Load Reductions by Day Type and Weather Year
All Residential Summer Saver Participants
Forecast Year 2012

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

Table 1-5
Average and Aggregate Load Reductions by Day Type and Weather Year
All Commercial Summer Saver Participants
Forecast Year 2012

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

Table 1-6
Average and Aggregate Load Reductions by Day Type and Weather Year
All Summer Saver Participants
Forecast Year 2012

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

2. INTRODUCTION AND PROGRAM SUMMARY

SDG&E's Summer Saver program is a demand response resource based on air conditioning load control. It is implemented through an agreement between SDG&E and Alternate Energy Resources, formerly known as Comverge, and is currently scheduled to continue through 2016. This report provides ex post load impact estimates for the Summer Saver program for 2009 and ex ante load impact forecasts for 2010 through 2020.

2.1. Program Overview

The Summer Saver program is available to residential customers and commercial facilities that use up to a maximum of 100kW on average during a 12-month period.[1] The event season for this program runs from May 1st through October 31st. Events cannot be less than two-hours or more than four hours in duration and cannot be triggered more than 40 hours in a program month or 120 hours in a program year. Events also cannot occur on holidays or on more than three days in any calendar week.

Summer Saver is classified as a "Day Of" demand response program. This program does not notify participating customers of an event. A Summer Saver event may be triggered the day of an event if warranted by temperature and system load conditions. SDG&E may call an event whenever the Company's electric system supply portfolio reaches resource dispatch equivalence of 15,000 Btu/kWh heat rate, or as utility system conditions warrant. A Summer Saver event may also be triggered as warranted by extreme system conditions such as special alerts issued by the California Independent System Operator, SDG&E system emergencies related to grid operations, or under conditions of high forecasted California spot market prices or for testing/evaluation purposes.

There are a variety of enrollment options for both residential and commercial customers. Residential customers can choose to be cycled 50% or 100% of the time, and can have cycling occur only on weekdays or on both weekdays and weekends. The incentive paid for each option varies. The 50% cycling option pays $11.50/ton of air conditioning capacity and the 100% cycling option pays $46/ton. The 7-day option pays an extra $10 for the summer. Thus, a residential customer with a 4 ton air conditioner would be paid the following under each option:

- $46 for the summer for the weekday, 50% cycling option;
- $56 for the 7-day, 50% cycling option;
- $184 for the weekday only, 100% cycling option; and
- $194 for the 7-day, 100% cycling option.

Commercial customers have an option of choosing 30% or 50% cycling, on weekdays only or for seven days a week. The incentive payment equals $9/ton for the 30% cycling option and $15/ton

[1] SDG&E is aware that there are exceptions to this rule. For instance there have been several schools signed up for Summer Saver whose demands exceed 100 kW.

for the 50% cycling option. As was true for residential customers, the incremental payment for the 7-day a week option compared with the weekday only option is $10. The average commercial participant has roughly 9 tons of air conditioning (although many participants have significantly more). As such, the incentive payment for the average commercial customer under each enrollment option is as follows:

- $81 for the summer for the weekday, 30% cycling option;
- $91 for the 7-day, 30% cycling option;
- $135 for the weekday only, 50% cycling option; and
- $145 for the 7-day, 50% cycling option.

Enrollment in the Summer Saver program as of February 2010 is summarized in Table 2-1. As of early 2010, there were 29,527 premises enrolled in the program, which in aggregate have roughly 144,000 tons of air conditioning capacity. Almost 82% of participants were residential customers, although these customers accounted for roughly two thirds of the total tons of cooling that are subject to control under the program. Roughly 48% of residential participants elected the 100 percent cycling option and about one quarter or residential customers chose to allow cycling on both week days and weekends. Almost 60% of commercial customers selected the 50 percent cycling option over the 30 percent option, but less than 5 percent of commercial customers chose to allow cycling on the weekend.

Table 2-1
Summer Saver Enrollment as of February 2010

Customer Type	Cycling Option	Day Option	Enrolled Customers	Enrolled Tons
Commercial	30%	Both	80	695
		Weekdays Only	2,079	17,731
		Total	2,159	18,426
	50%	Both	172	1,410
		Weekdays Only	3,061	27,554
		Total	3,233	28,965
	Total		5,392	47,391
Residential	50%	Both	848	3,330
		Weekdays Only	11,768	45,202
		Total	12,616	48,531
	100%	Both	5,725	23,495
		Weekdays Only	5,794	24,873
		Total	11,518	48,368
	Total		24,135	96,899
Grand Total			29,527	144,290

Table 2-2 shows the expected increase in enrollment in the Summer Saver program through the end of 2011. Summer Saver enrollment is expected to increase to roughly 169,000 tons of air conditioning by the end of 2011, a growth of about 17%, and then remain constant from 2012 through 2020. Enrolled capacity is expected to grow faster in the residential sector (19%) compared with the commercial sector (13%). The average load reduction will increase over this period as a result of the much greater forecasted enrollment in the residential 100% cycling option (35% growth) compared with the 50% cycling option (3%). Growth in the commercial 50% cycling option (15% growth) is also expected to be greater than growth in the 30% cycling option (11%).

Table 2-2
Summer Saver Enrollment Projections
(air conditioning tons)

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

2.2. 2009 Summer Saver Event Summary

In 2009, seven Summer Saver events were called. Table 2-3 shows the dates and timing of each event. All residential and commercial accounts were called for each event. All called events were four hours long and each one began either at 1 pm, 1:30 pm or 2 pm.

Table 2-3
Summer Saver 2009 Event Summary

Date	Day of Week	Start	End
7/21/2009	Tuesday	1:00 PM	5:00 PM
8/26/2009	Wednesday	1:00 PM	5:00 PM
8/27/2009	Thursday	1:30 PM	5:30 PM
8/28/2009	Friday	1:30 PM	5:30 PM
9/2/2009	Wednesday	2:00 PM	6:00 PM
9/3/2009	Thursday	2:00 PM	6:00 PM
9/24/2009	Thursday	1:00 PM	5:00 PM

2.3. Load Research Sample Summary

The Summer Saver load impact analysis was based on the end use level data from the sample of residential and commercial customers described below. Whole building data was used to estimate load impacts for residential and commercial customers in order to compare the predicted values based on the two forms of data.

SDG&E has deployed dual-socket metering at approximately 280 residential Summer Saver participants' electric metering points. The dual socket adaptors hold two interval data recording meters, one recording whole-house energy usage, and another recording the energy usage of a single air conditioner. These meters were deployed over the course of three years. In 2006, 50 homes were metered. In 2007, 150 homes were metered, and in 2008 an additional 80 homes were metered. The 2006 installations were the result of a stratified sampling design, with tonnage used as the stratifying variable. Tonnage did not prove to correlate well with recorded air conditioner energy usage, so that strategy was not adopted in 2007 and 2008. Furthermore, meeting strata quotas proved difficult to manage because it was sometimes difficult to install the complicated equipment on some selected premises. Consequently, the 2007 and 2008 residential samples were developed using a simple random sampling plan. The residential sample was divided into two groups, A and B. During each of the seven program events in 2009, only one group was cycled, with the selected group alternating from one event to the next (e.g., during event 1, Group A would be cycled and Group B would not be cycled, then during the next event, Group B would be cycled and not Group A).

The commercial Summer Saver sample was drawn in early 2009, when the participant population consisted of 4,297 premises with between one and 113 devices installed at the site. The total number of devices was 9,881. Premises had either single- or three-phase power supplying the units on which the devices were installed. In addition, there were the two cycling levels described in the prior section at which program participants were participated (50 and 30 percent). SDG&E stratified the population by phase, cycling level and usage. Table 2-4 shows the breakdown of the population and sample at the time the sample was drawn.

Table 2-4
Commercial Participant Population and Sample as of Early 2009

Phase	Cycling Strategy	Number of Units	Population		Sample – Installed	
			Premises	Devices	Premises	Loggers
Single	30	1	247	247	11	11
		2	86	172	8	8
		3-5	45	163	9	9
		6-10	12	86	4	4
		11-21	1	16	0	0
		22-40	1	32	1	2
	50	1	291	291	14	14
		2	114	228	11	11
		3-5	60	218	10	10
		6-10	21	153	7	7
		11-21	4	56	2	2
Three	30	1	756	756	36	36
		2	299	598	30	30
		3-5	203	727	36	36
		6-10	61	455	22	22
		11-21	18	258	10	10
		22-40	5	139	2	4
		41-57	1	57	0	0
	50	1	1,110	1,110	58	58
		2	464	928	49	49
		3-5	321	1,169	63	63
		6-10	119	895	42	42
		11-21	46	669	17	17
		22-40	8	209	5	10
		41-57	3	136	2	6
		58-113	1	113	0	0
Total			4,297	9,881	449	461

This commercial sample provides each device an approximately equal probability of being selected. Given the population and sample size, one of every 21.5 devices was included in the sample. Premise quotas within a stratum were determined based on this probability. For premises with more than 21 devices, the sample was structured so as to "round up" the number of units with loggers, slightly increasing the probability of an individual device from this group being included in the sample.

The final commercial customer sample has 449 premises with 461 loggers. The installed stratum counts closely match the design quotas. For the strata including premises with more than 21 devices, the population includes 13 sites. Multiple loggers were successfully installed at 10 of these sites. The only stratum falling well short of its quota was the three-phase, 50 percent cycling stratum for premises with between 11 and 21 devices. Because of the large number of devices at these sites, the premise-level quota was higher than expected (67 percent of the premises) with the intent of obtaining as many of these sites as possible. Despite falling short of the target quota, the installers did succeed in installing loggers at 37 percent of the available premises in this stratum.

The commercial sample was divided into three groups, A, B and C. During each event operation, two of the three groups were cycled, with the third acting as a control. Groups A and B were cycled on alternating events, while Group C was cycled on all events.

2.4. Report Structure

The remainder of this report contains three sections. Section 3 covers the residential sector analysis. It begins with a discussion of the analysis approach that was used to develop both the ex post and ex ante load impact estimates. This is followed by a presentation of the ex post analysis. In addition to providing load impact estimates for each event day, which are based on the end use load research data discussed above, a comparison is made between estimates based on these data and estimates based on analysis of whole building loads. This comparison is important since, if the two methods produce similar values, it may be possible for SDG&E to base future impact estimates on whole building data, which will be available on all customers once SDG&E's smart meter deployment is complete. The ex post analysis also summarizes the distribution of impacts across customers, identifying, for example, the percent of customers that provide little or no load reduction and the percent that provide significant load reductions. This analysis is potentially useful for improving program cost-effectiveness, as it can be used to identify the characteristics of low and high users as input to targeted marketing efforts for future enrollment. Section 3 also presents ex ante load impact estimates for 2010 through 2020. This section conforms to the requirements of the CPUC Load Impact Protocols,[2] which requires that estimates be provided for selected day types and different weather conditions. The final subsection contains recommendations for future program evaluations.

Report Section 4 covers the commercial sector and is organized similarly to Section 3. Section 5 contains a brief summary of ex post and ex ante load impacts for the program as a whole.

[2] D08-04-050. Decision Adopting Protocols for Estimating Demand Response Load Impacts. Appendix A. April 24, 2008.

3. RESIDENTIAL SECTOR LOAD IMPACT ANALYSIS

This report section summarizes the ex post and ex ante load impacts for residential customer participants in SDG&E's Summer Saver program. As described in Section 2, seven events were called in 2009. As required by the CPUC Load Impact Protocols, load reductions are reported for each ex post event and for the average event. Ex ante load impact estimates have been generated for each monthly system peak day based on both 1-in-2 and 1-in-10 year weather conditions for each forecast year from 2010 through 2020. Hourly estimates are provided in tables filed electronically in conjunction with this report. Selected summary values are contained in this chapter.

3.1. Analysis Methodology

The impact estimates for residential customers were based on end use data. A model with whole house data was also estimated for comparison purposes. The end use analysis methodology is presented first and the whole house analysis methodology is discussed at the end of this section.

In total, 279 accounts were selected from SDG&E's full residential participant population for the 2009 Summer Saver program evaluation. The sample design and selection process was described in Section 2. The final estimation was based on data from 276 individual air conditioning units.[3]

The sampled customers were divided into two groups so that each event day had a comparison group that was not called and a curtailed group that was called. Of the 276 customers in the final estimating sample, 139 were in group A and 137 in group B. As shown in Table 3-1, groups A and B alternated between the curtailed and comparison groups from one event to the next. The comparison group was useful because it helped determine which regression model to use. If a model performed well for the comparison group on actual event days, we could be confident that estimates of the reference load for the curtailed group were accurate.

Table 3-1
Event Dates, Times, and Groups Called in Residential Sample

Event Date	Start Time	End Time	Group Called
7/21/2009	1:00 PM	5:00 PM	A
8/26/2009	1:00 PM	5:00 PM	B
8/27/2009	1:30 PM	5:30 PM	A
8/28/2009	1:30 PM	5:30 PM	B
9/2/2009	2:00 PM	6:00 PM	A
9/3/2009	2:00 PM	6:00 PM	B
9/24/2009	1:00 PM	5:00 PM	A

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

The residential regressions were developed using a GLS estimator with robust standard errors. The following equation summarizes the specification of the model used to estimate air conditioning load based on end use load data:

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

In this equation,

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

α_o = Estimated constant term;

β_{ij} through θ_m are the estimated coefficients;

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

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

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

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

CDD^2 = CDD squared

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

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

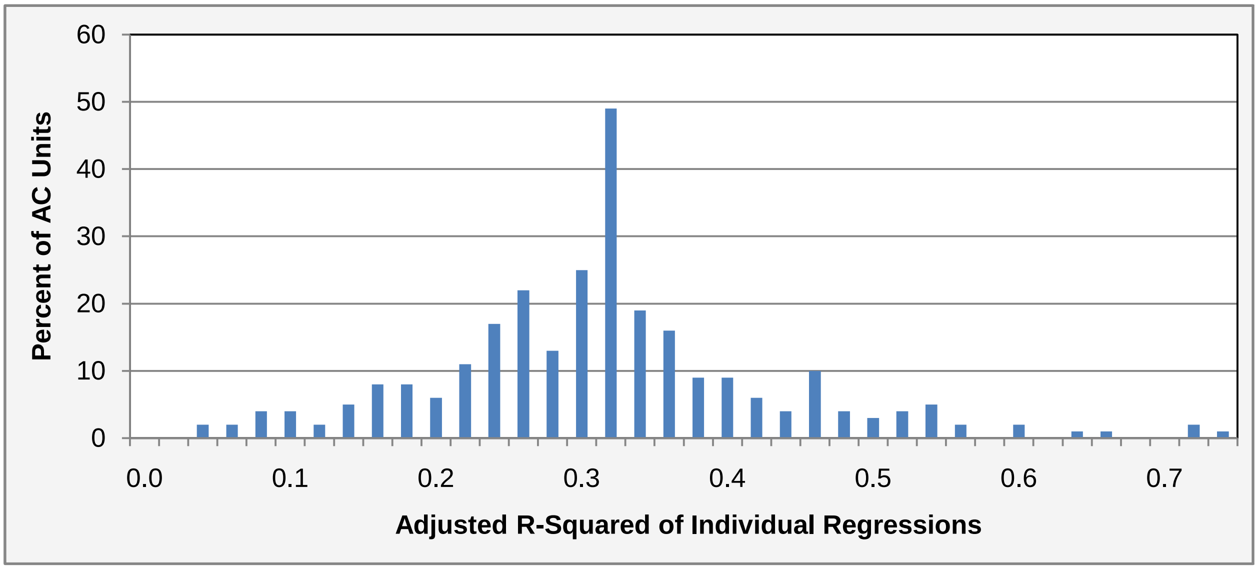
$POSTEVENTHOUR_m$= Series of binary variables representing twelve half-hour time periods immediately following the end of an event (1-12);

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

ε = the error term.

Figure 3-1 shows the distribution of R-squared values for the individual air conditioning unit regressions. Around one-third of individual regressions have R-squared values less than 0.25, whereas the upper one-third have R-squared values exceeding 0.34. Even though some of the individual R-squared values are low, the model explains nearly 95 percent of the variation in aggregate load when the predicted and actual values are aggregated by day and half-hour. Within each cycling strategy, the model explains around 94 percent of aggregate load.

Figure 3-1
Distribution of R-squared Values from Individual Regressions based on Residential End Use Load Data



With any load impact analysis, the most important feature is the ability to accurately predict load and load reductions under event conditions for which demand response is designed to provide a reliable resource. This load impact analysis is unique because a portion of the sample was not curtailed on each event day. Therefore, we can determine the accuracy of the reference load by comparing predicted and actual load for the comparison group on actual event days. Similarly, since participants in air conditioning load control programs are not notified of a pending event, there is no possibility of any load shifting to pre-event hours, and predicted and actual load for the curtailed group should match up closely in the hours leading up to the event.

Figure 3-2 compares the predicted and actual hourly air conditioning load of the comparison group for the average event day. The model accurately predicts air conditioning load of the comparison group. The average error throughout the day is 5.7 percent. More importantly, the average error during the peak period from 1 to 6 pm is 3.7 percent.

Figure 3-3 compares the predicted and actual hourly air conditioning load of the curtailed group for the average event day. The average error during event hours it is 4%. Given that there are event and post-event variables in the model, it is expected that the model predicts well during those hours. In the hours leading up to the event, there are no event variables and the model also performs well. From 10 am to 1 pm, the average error is 2.5 percent.

Figure 3-2
Predicted and Actual Residential Air Conditioning Load for the Average Event Day Comparison Group

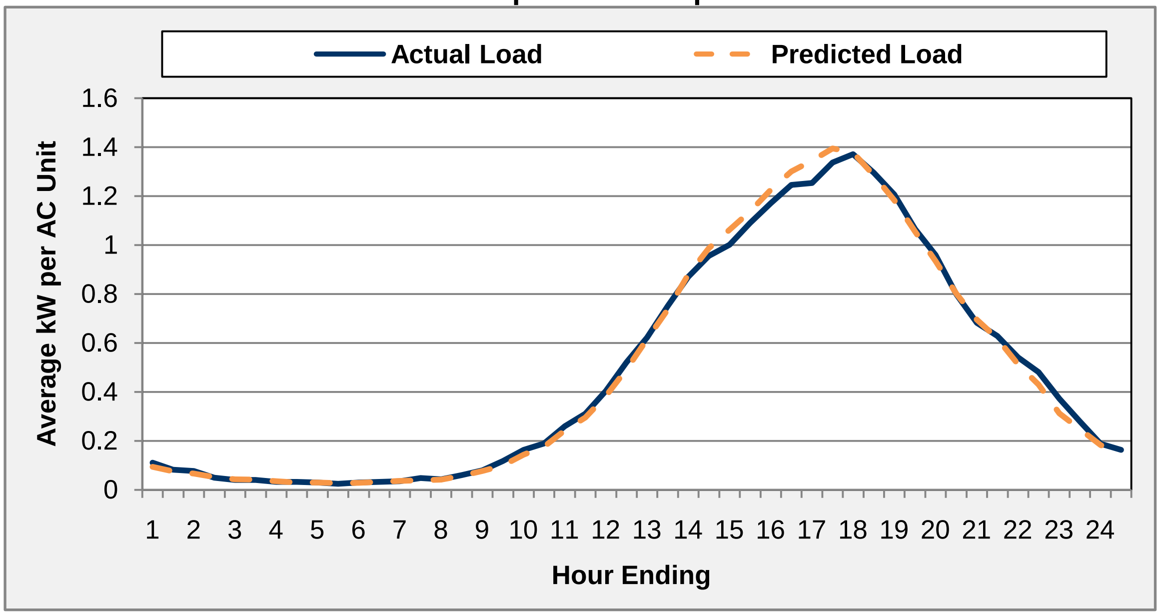


Figure 3-3
Predicted and Actual Residential Air Conditioning Load for the Average Event Day Curtailed Group

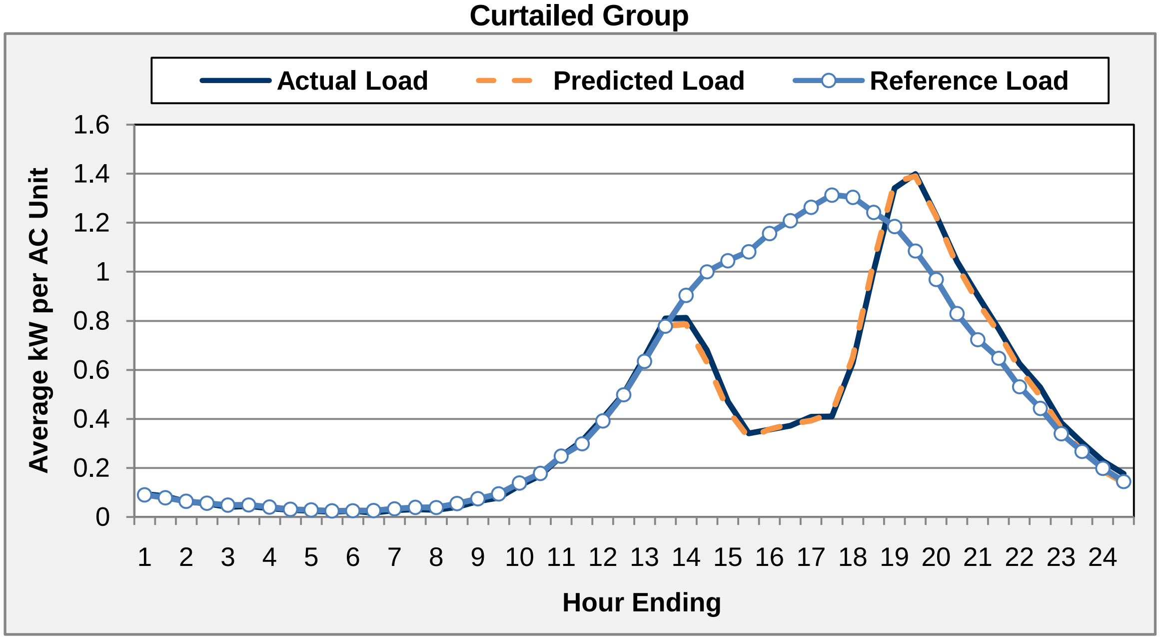
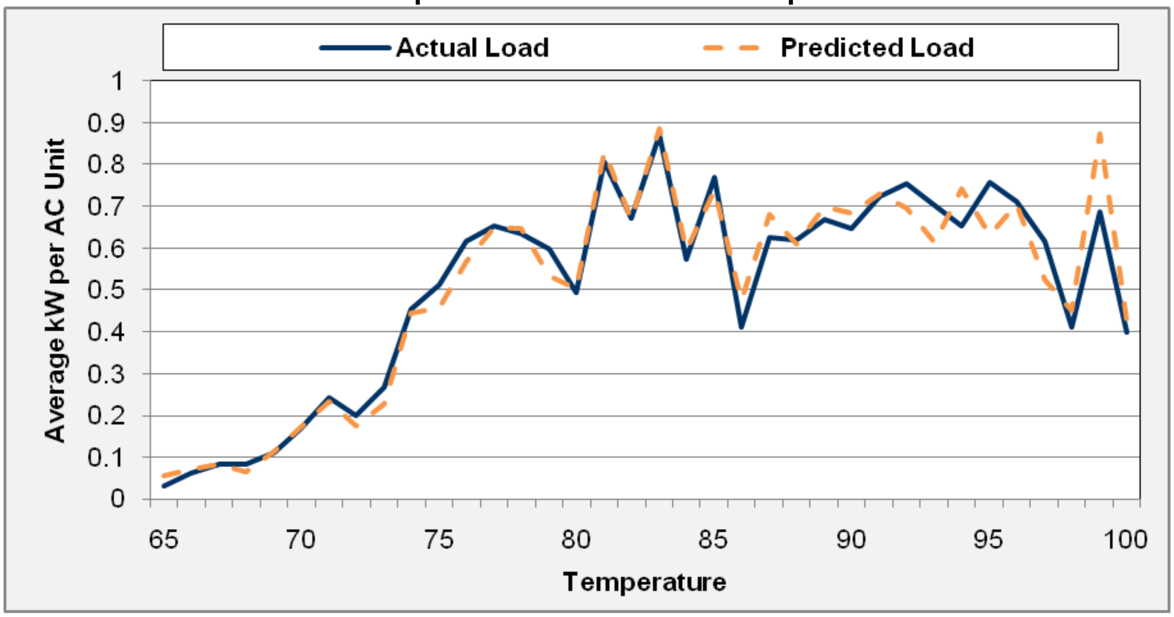


Figure 3-4 compares the predicted and actual air conditioning load by temperature on event days. This figure illustrates that the model predicts relatively well across a range of temperatures. From 80 to 100 degrees, the average error is 7.6 percent.

Figure 3-4
Predicted and Actual Residential Air Conditioning Load by Temperature on Event Days
Comparison and Curtailed Groups



The whole house model was nearly the same as the air conditioning model except that binary variables for each half-hour were included in order to capture variation in load that is not sensitive to weather. The whole house load impact estimates are compared to the air conditioning estimates in Section 3.2.4. Although the final results are based on the air conditioning model, it is important to see how well the whole house model predicts in order to understand why there are some differences between the AC and whole house estimates.

Figure 3-5 compares the predicted and actual hourly whole house load of the comparison group for the average event day. Figure 3-6 compares the predicted and actual hourly whole house load of the curtailed group for the average event day. As shown in the figures, the whole house model also predicts well for the comparison and curtailed groups on event days.

Figure 3-5
Predicted and Actual Residential Whole House Load for the Average Event Day Comparison Group

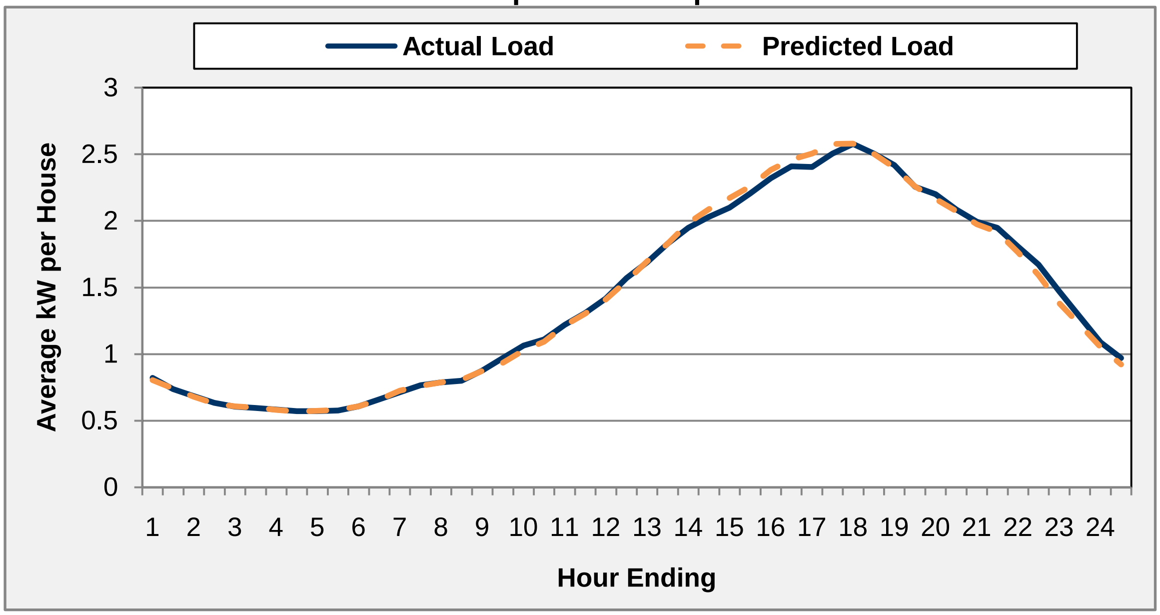
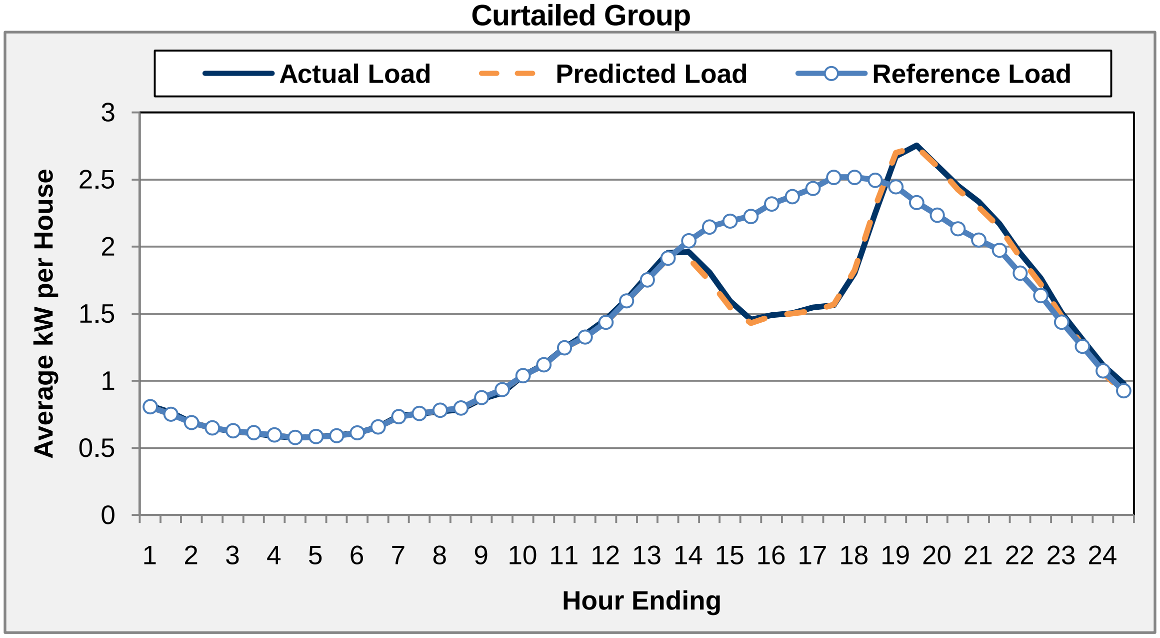


Figure 3-6
Predicted and Actual Residential Whole House Load for the Average Event Day Curtailed Group



3.2. Ex Post Load Impact Estimates

This section presents load impact estimates for residential customers for each event day that occurred in 2009. A distributional analysis, showing the percent of customers who provide load impacts exceeding selected thresholds, is presented in Section 3.2.2. Section 3.2.3 shows how impacts vary between CARE and non-CARE customers and Section 3.2.4 compares load impacts based on end-use interval data with impacts estimated using premise level interval data.

3.2.1. Event Day Load Impact Estimates

Tables 3-2 and 3-3 show the load impacts for each event, and for the average event, in 2009. Table 3-2 reports the average values per customer and Table 3-3 reports the average values per ton of air conditioning. Each table shows enrollment on each event date, the reference load per customer or per ton, the average load with load control in effect, the average absolute and percent load reduction, the aggregate load reduction and the average temperature. Recall from Section 2 that roughly half of residential customers and half of the enrolled air conditioning tonnage selected the 100% cycling option.

The average load reduction across the four-hour event window[4] and across the seven event periods is 0.63 kW per air conditioning unit, or 0.18 kW per ton. The average reduction equaled roughly 55% of the typical reference load. The first and last events had the lowest average load reduction and were also the only stand alone events. The remaining events were called three days in a row in August and two days back-to-back in early September. The absolute average load reduction was highest on the second and third days of the August event sequence and on the second day of the two-day September sequence, suggesting that more air conditioning units were probably operating at higher duty cycles when system conditions warranted that events were called several days in a row.

The average aggregate load impact across the seven events was 17.3 MW, and ranged from a low of 12.8 MW on July 21st to a high of 20.2 MW on August 27th. These aggregate estimates are based on program enrollment of approximately 24,000 residential accounts and almost 96,000 tons of air conditioning. Enrollment changed very little over the course of the two months in 2009 during which events were called.

[4] Recall from Section 2 that each event lasted four hours, but the event start time was either at 1 pm, 1:30 pm or 2 pm.

Table 3-2
Average Hourly Load Reduction for Event Period by Event Day
All Residential Summer Saver Customers, kW per AC Unit[5]

Date	Day of Week	Enrolled Participants	Avg. Reference Load (kW)	Avg. Estimated Load w/DR (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	23,197	0.86	0.38	0.48	55.9	12.8	85.3
8/26/2009	W	24,065	0.98	0.35	0.63	64.1	16.9	90.6
8/27/2009	Th	24,065	1.32	0.60	0.73	54.9	20.2	92.9
8/28/2009	F	24,065	1.13	0.39	0.74	65.7	19.9	92.5
9/2/2009	W	24,064	1.31	0.72	0.59	45.4	16.5	86.4
9/3/2009	Th	24,064	1.31	0.61	0.69	53.0	18.6	88.3
9/24/2009	Th	24,111	1.10	0.54	0.57	51.2	15.9	90.2
Average Event	**N/A**	**23,947**	**1.14**	**0.51**	**0.63**	**55.3**	**17.3**	**89.5**

Table 3-3
Average Hourly Load Reduction for Event Period by Event Day
All Residential Summer Saver Customers, kW per Ton of Air Conditioning

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

[5] In this table, the aggregate load reduction does not equal the number of enrolled participants times the average load reduction. SDG&E records enrollment according to the number of customers and the total amount of air conditioning tonnage. However, the load research sample records usage per air conditioning unit. Enrolled participants in this table equal the number of premises in the program whereas the average reference load and load reduction values are based on the load research sample and represent the average air conditioning unit. To obtain the aggregate values, the average values per ton from Table 3-2 are multiplied by the number of air conditioning tons.

Table 3-4 shows the average reference load and load impact by cycling option for residential Summer Saver customers. It is interesting to note that customers who chose the 50% cycling option had significantly higher average reference loads (more than one third higher) than those who chose the 100% cycling option. This selection effect is not surprising, since it is more likely that customers that use their air conditioning more place a higher value on it and, therefore, are less likely to select a program option that shuts their air conditioner down completely on high use days. Given this, the average load reduction per ton of air conditioning for the 50% cycling group is only 27% less than for the 100% cycling group, even though the percent reduction for the 50% cycling group is roughly half that of the 100% cycling group. The aggregate load reduction for the 50% cycling group is only 25% less than for the 100% cycling group, because more customers with higher loads selected the lower cycling option.

Table 3-4
Average Hourly Load Reduction for Event Period by Cycling Option
(2009 Ex Post Load Impacts for Residential Sumer Saver Program Participants)

Cycling Strategy	Avg. Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Hourly Load Reduction (MW)
50% Cycling	49,972	0.37	0.23	0.15	39.7	7.4
100% Cycling	45,717	0.27	0.06	0.21	78.6	9.8
All Residential	**95,690**	**0.33**	**0.15**	**0.18**	**55.3**	**17.3**

In light of the above findings, it is interesting to assess the relative cost effectiveness of customers on the 50% and 100% cycling strategies, given the current program incentive structure. Recall from Section 2 that a customer with a four-ton air conditioner and weekday only cycling option would be paid $46 per season for the 50% cycling option and $184 per season for the 100% cycling option. Assuming that the installed cost for an air conditioning switch is $150 (and ignoring any recruitment costs), the cost over three seasons for each cycling option would equal $288 for the 50% option and $702 for the 100% cycling option. Over five years, the costs would equal $380 and $1,070, respectively. As such, over a three year period, the costs for the 50% cycling group are 60% less than for the 100% cycling group, while the benefits (in terms of the avoided cost of capacity) would only be about 30% less (as determined by the relative average load reduction for the two groups—0.52/0.76 = 0.68). Over five years, the costs for the 50% cycling group are 65% less than for the 100% cycling group. In light of the above examples, it is likely that program cost effectiveness could be improved by increasing the share of 50% cycling customers relative to 100% cycling customers (assuming that the load profile of the two groups remained the same—that is, that new recruits into the 50% cycling group had higher reference loads as they do among the current population). Alternatively, cost-effectiveness could be improved by reducing the incentive paid to the 100% cycling group.

3.2.2. Distribution of Load Impacts

Table 3-5 shows the distribution of residential customers by cycling option who provide load impacts exceeding selected thresholds. As seen, on average, roughly 25% of all participating customers provided no load reduction at all over the seven event days in 2009 while more than one third provided load reductions that exceeded 0.20 kW/ton. Recall from Table 3-3 that the average reduction across all residential customers equaled 0.18 kW/ton. As seen in Table 3-5, roughly 40% of customers provided load reductions that exceeded the average for the program. Customers who did not provide any load relief during events in 2009 had a roughly equal likelihood of selecting the 50% or 100% control option.[6] On the other hand, as expected, the percent of customers that exceeded the higher thresholds is much greater for the 100% cycling option than for the 50% cycling option.

Table 3-5
Share of Residential Summer Saver Air Conditioning Tonnage That Provides Load Reductions Exceeding Selected Thresholds

Customer Category	Share of Accounts (%) Providing Load Reductions Greater Than:					
	0.0 kW/Ton	0.1 kW/Ton	0.2 kW/Ton	0.3 kW/Ton	0.4 kW/Ton	0.5 kW/Ton
Residential - 50% Cycling	74.4	57.3	34.9	17.7	9.0	5.3
Residential - 100% Cycling	77.3	52.4	42.2	31.3	25.3	17.8
All Residential Customers	**75.8**	**55.0**	**38.3**	**24.1**	**16.6**	**11.2**

In an effort to determine whether high responders can be identified and targeted in future marketing efforts, a regression model was estimated that relates the load impact per ton of air conditioning to information available on all customers. The regression results are summarized in Table 3-6. The dependent variable is the load reduction (kW/ton) for each event for a given customer. The definitions for the explanatory variables should be clear from their description in the table, with the possible exception of the correlation variable shown in the first table row. This variable equals the correlation between monthly customer electricity use and monthly cooling degree hours. This is a proxy for air conditioning energy use.

[6] Slightly fewer customers on the 100% cycling option provided no load reduction during the seven events.

Table 3-6
Selected Variables from Regression Analysis of kW per Ton Load Reductions[7]
2009 Event Days

Variable	Coefficient	T-Statistic	P-Value	95% Confidence Interval	
Correlation (Monthly kWh and CDH)	0.22	8.48	0.00	0.17	0.27
Temperature During Event Hours	0.01	2.37	0.02	0.00	0.01
100% Cycling Group	0.07	1.69	0.09	-0.01	0.15
Weekday Only Option	-0.02	-0.61	0.54	-0.10	0.05
Effective Date in Program	0.00	-1.62	0.11	0.00	0.00
CARE Customer	0.06	1.27	0.21	-0.03	0.14
Climate Zone 2	0.02	0.11	0.91	-0.28	0.31
Climate Zone 4	-0.04	-0.68	0.50	-0.16	0.08
Monthly Summer kWh	0.00	-1.47	0.14	0.00	0.00
AC Unit Tons	-0.01	-0.48	0.63	-0.04	0.02

As is evident in Table 3-6, the primary driver of load impacts is the correlation between electricity use and cooling degree hours—in other words, the key driver is the variable that best represents the amount of air conditioning use that occurs on average over the summer period. While this result should not be surprising, the magnitude and high statistical significance of the variable is important. This variable can be calculated for any customer, as it relies on data that are available on all customers. Targeting customers with a high value for this variable in future marketing campaigns could improve overall load response. The other two statistically most significant variables are the temperature during event hours and whether or not a customer is in the 100% cycling group. Both of these variables have positive coefficients, although neither coefficient is large compared with the coefficient on the correlation variable and the 100% cycling variable is not statistically significant at the 95% confidence level. It is worth noting that the variable representing air conditioning size is highly insignificant and has a coefficient that is very close to 0. This indicates that once you control for weather sensitive electricity use (represented by the correlation variable), there is no incremental load reduction provided by customers with larger air conditioners.

Table 3-7 shows the distribution of load impacts provided by customers stratified by the correlation between electricity use and weather. Customers in the 1st quintile are those who have a low correlation between weather and electricity use (that is, those who use their air conditioning very little) while those in the 5th quintile have a very high correlation, indicating a large amount of air conditioning energy use. Only 10% of customers in the top quintile provided no load reduction over the seven events in 2009, whereas 40% of customers in the 1st quintile provided no demand response. At the other end of the spectrum, almost no one in the lowest quintile provided load reductions exceeding 0.5 kW/ton, whereas almost one quarter of customers in the top quintile provided load reductions exceeding this threshold.

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[7] Robust standard errors are used to calculate the t-statistics and p-values. The overall r-squared value is 0.19. Although coefficients for a constant term and individual event dummy variables were estimated and controlled for in the model, only the output for key explanatory variables is shown.

Table 3-7
Share of Commercial Customers Exceeding Load Reduction per Ton Thresholds by Quintiles of Correlation Variable

Quintile of Correlation (Monthly kWh and CDH)	Share of Accounts (%) Providing Load Reductions Greater Than:					
	0.0 kW/Ton	0.1 kW/Ton	0.2 kW/Ton	0.3 kW/Ton	0.4 kW/Ton	0.5 kW/Ton
1st	61.5	28.6	12.8	8.6	0.8	0.8
2nd	64.0	51.0	32.5	15.7	8.7	4.1
3rd	84.4	59.6	30.6	21.2	17.4	15.3
4th	84.5	77.2	65.1	37.7	27.4	15.1
5th	90.1	70.3	62.9	44.4	35.7	24.6
All	**74.2**	**55.0**	**38.3**	**24.1**	**16.6**	**11.2**

3.2.3. Load Impacts for CARE and Non-CARE customers

Another interesting distributional examination of load impacts involves comparing load impacts between CARE and non-CARE customers. 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. Qualification for CARE is based on self-reported, household income and varies with the number of persons per household. CARE customers often volunteer for energy efficiency and demand response programs at different rates than do non-CARE customers and sometimes have different load profiles and response rates than non-CARE customers.

Table 3-8 compares the load impact estimates for CARE and non-CARE customers. CARE customers account for roughly 13% of enrolled participants in the Summer Saver program, and about 11% of residential air conditioning tonnage. CARE customers have higher reference loads (on a kW/ton basis) than do non-CARE customers, and provide greater absolute and percent load reductions. There are several reasons why this might be true. The average air conditioning tons per customer equals 3.45 for CARE customers and 4.08 for non-CARE customers. This suggests that CARE customers either live in smaller houses, have air conditioners that are undersized (relative to non-CARE customers), or both. An under sized air conditioner will run more frequently at a given temperature than will one that is over sized. It may also be that CARE customers have less efficient air conditioning units and less insulation in their homes, both of which would cause the air conditioner to run more frequently and to use more electricity per unit of operation. Whatever the cause of these differences, CARE customers appear to be attractive targets in terms of the average load reduction they produce.

Table 3-8
Load Impacts for CARE and Non-CARE Customers

CARE Status	Avg. Enrolled Participants	Avg. Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Hourly Load Reduction (MW)
Non-CARE Customers	20,918	85,234	0.32	0.14	0.17	54.6	14.7
CARE Customers	3,029	10,455	0.44	0.18	0.27	60.0	2.8
All Customers	**23,947**	**95,690**	**0.33**	**0.15**	**0.18**	**55.3**	**17.3**

3.2.4. Comparison of End Use and Whole Building Load Impact Estimates

An important consideration for future program evaluations is whether load impacts can be accurately estimated using load data for the entire residential premise rather than using the end-use data that underlie the load impacts presented here. Obtaining end use air conditioning load data is expensive as it requires paying a representative sample of customers to allow data loggers or dual socket meters to be installed, installing the equipment and retrieving the data at the end of the program season. If accurate load estimates could be obtained from whole house data, once all of SDG&E's smart meters are installed, it would be possible to estimate load impacts based on a much larger and potentially more representative sample of customers at much lower cost than can be done through end use data collection. Given that SDG&E installed dual channel data loggers on the sample of residential households used for this analysis, it was possible to compare estimates based on end use and whole premise level data analysis in order to determine the accuracy of the whole premise level analysis.

Table 3-8 contains estimates of load impacts for the average residential participant as well as for the average participant in each of the two cycling groups based on end use and whole house data. As seen, the estimates based on the whole house data are essentially identical to those obtained from the end-use data for the two groups combined, as well as for the 100% cycling group. The small differences that exist are in the third decimal point of the estimated values. The difference is slightly larger for the 50% cycling group, although they are still quite close. The primary reason that the comparisons for the 50% cycling group are not as close as for the other two comparison groups is that the "signal to noise" ratio is lower for those on 50% cycling than for those on 100% cycling. By this, we mean that the magnitude of the impact of air conditioner cycling (the signal) is smaller under 50% cycling relative to the variation in load across hours than it is under 100% cycling and, therefore, is more difficult to isolate using regression analysis than when the impact is larger. However, the accuracy of the estimates using whole building data is still very high. The difference in the comparisons is in the third decimal point on two of the seven event days. On the three worst days, the difference equals roughly 0.03 kW/ton. Overall, the difference between the two estimates is roughly 6%, with the estimates based on the whole building data being slightly less than those based on the end-use data.

Table 3-9
Comparison of Residential Load Impact Estimates Based on End-Use and Whole Building Data (Unweighted data)[8]

Event Date	Both Groups		50% Cycling Group		100% Cycling Group	
	AC Impact (kW/Ton)	WH Impact (kW/Ton)	AC Impact (kW/Ton)	WH Impact (kW/Ton)	AC Impact (kW/Ton)	WH Impact (kW/Ton)
7/21/2009	0.17	0.17	0.15	0.15	0.18	0.18
8/26/2009	0.21	0.21	0.14	0.11	0.24	0.24
8/27/2009	0.26	0.26	0.22	0.22	0.27	0.27
8/28/2009	0.25	0.24	0.16	0.13	0.28	0.29
9/2/2009	0.21	0.21	0.18	0.18	0.22	0.22
9/3/2009	0.23	0.23	0.15	0.12	0.26	0.27
9/24/2009	0.20	0.20	0.19	0.18	0.20	0.20
Average Event	0.22	0.22	0.17	0.16	0.24	0.24

It should also be noted that once smart meters are installed everywhere, estimates derived from whole building data can be based on much larger samples of customers and on samples that can always be made to be representative of the current program population. A challenge with basing estimates on end use data is that sample sizes must be kept relatively small in order to keep costs under control and must also be chosen several months before the start of the program operating season to allow time to recruit customers and install the end-use data loggers. Both of these factors mean that there is a risk that samples may not be completely representative of the population of interest when events are called. Although population weights can be used to make adjustments when populations change over the course of a summer, any small sample is more subject to sampling bias than are larger samples. When smart metering is ubiquitous, much larger samples can be drawn and used for estimation purposes, which will reduce any risk of sampling bias and also reduce the standard errors of the estimated model coefficients.

3.3. Ex Ante Load Impact Estimates

The models developed from the ex post load data in 2009 were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2010 through 2020. FSC was provided with data by SDG&E that represents weather under 1-in-2 and 1-in-10 year conditions for each monthly system peak day and a typical event day.[9] SDG&E also provided enrollment estimates by customer type and cycling option, which were presented in Table 2-2. As indicated in Section 2, the program is forecasted to reach a steady state by the end of 2011, with future enrollment equal to attrition. As such, the last year in which load impact estimates change

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[8] The values in each cell of this table would change if the data were weighted, but the differences would be the same on a percentage basis and the conclusions would also be the same. Values in this table should not be compared with those in Table 3-2, which are based on weighted estimates.

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

is 2012. Ex ante estimates for 2013 through 2020 are the same as for 2012. The ex ante event window chosen by SDG&E is from 1 to 6 pm.[10]

Table 3-10 summarizes the average load impact across the five hour event window for each monthly system peak day and for the typical event day, under 1-in-2 and 1-in-10 year weather conditions based on the steady state enrollment levels reached by the beginning of 2012. Load impact estimates are presented for the average air conditioning unit, for each ton of air conditioning and for all residential participants as a whole. For a typical event based on 1-in-2 year weather conditions, the average reduction per air conditioning unit is 0.52 kW, and the reduction average per ton of air conditioning is 0.15 kW. Based on 1-in-10 year weather conditions, these values are roughly 18% higher (0.61 kW and 0.17 kW/ton, respectively). The aggregate program load reduction potential is 17.0 MW for a typical event day under 1-in-2 year weather conditions, and 20.1 MW under 1-in-10 year weather conditions. These values are based on program enrollment equal to 115,441 tons of air conditioning.

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

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

Table 3-10
Average and Aggregate Load Reductions by Day Type and Weather Year
All Residential Customers
Forecast Year 2012

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

Table 3-11 shows the aggregate load impacts for each month in the years from 2010 through 2012. Enrollment for a typical event day, based on air conditioning tonnage, grows by about 14.2% over the three-year period while aggregate load impacts grow by 15.9% and 16.9% based on 1-in-2 and 1-in-10 year weather conditions, respectively. The reason load impacts are projected to grow faster than enrollment is that the majority of new participants are projected to select the 100% cycling option.

Table 3-11
Aggregate Load Reductions by Day Type, Weather Year and Forecast Year
All Residential Customers

Forecast Year	Day Type	Projected Tons	Aggregate Load Reduction (MW)	
			1-in-2 Year	1-in-10 Year
2010	Typical Event Day	101,086	14.7	17.2
	May Monthly Peak	97,498	10.6	11.5
	June Monthly Peak	98,694	3.2	15.9
	July Monthly Peak	99,890	12.9	16.6
	August Monthly Peak	101,086	15.1	18.4
	September Monthly Peak	102,282	18.4	20.6
	October Monthly Peak	103,479	15.0	15.9
2011	Typical Event Day	112,451	16.6	19.5
	May Monthly Peak	110,656	12.3	13.4
	June Monthly Peak	111,254	3.5	18.3
	July Monthly Peak	111,852	14.6	18.8
	August Monthly Peak	112,451	17.0	20.8
	September Monthly Peak	113,049	20.6	23.1
	October Monthly Peak	113,647	16.6	17.7
2012 to 2020	Typical Event Day	115,441	17.0	20.1
	May Monthly Peak	115,441	12.9	14.0
	June Monthly Peak	115,441	3.6	19.1
	July Monthly Peak	115,441	15.2	19.5
	August Monthly Peak	115,441	17.5	21.4
	September Monthly Peak	115,441	21.1	23.6
	October Monthly Peak	115,441	16.9	18.0

3.3.1. Load Impacts by Hour

Figures 3-7 and 3-8 contain the standard output tables required by the CPUC Load Impact Protocols for the average residential customer and all residential customers combined for the typical event day based on 1-in-2 year weather conditions and 2012 enrollment. Electronic versions of these tables for various day types and weather conditions have been filed along with this report.

Table 3-12 shows how load impacts vary across the five-hour event window for each required ex ante day type and set of weather conditions based on 2012 enrollment. There is significant variation in load impacts across event hours, monthly system peak days and weather conditions. For all days and weather conditions, load impacts are lowest in the first event hour, often significantly so. This reflects the generally mild climate in the San Diego region, where air conditioning is often not needed until later in the afternoon. For most day types and weather conditions, the largest load impact is in the last hour of the event period, from 5 to 6 pm, although this is not universally true (see, for example, the last hour on the August monthly peak day under 1-in-10 year weather conditions). For the typical event day under 1-in-2 year weather conditions, the load impact in the final event hour is 75% higher than the load impact in the first hour. The highest hourly load impact under 1-in-2 year weather conditions, 24.6 MW during the hour from 5 to 6 pm on the September peak day, is 45% greater than the average impact across all hours on a typical event day. Based on 1-in-10 year weather conditions, the peak hour is 38% higher than the average impact across all hours on a system peak day. Such comparisons highlight the variable nature of load impacts for air conditioner cycling, and the fact that load impacts for this type of resource are significantly higher on day types and under weather conditions when they have the highest probability of being called.

Table 3-12
Aggregate Load Reductions by Day Type, Weather Year and Hour
All Residential Customers, 2012 Enrollment

Weather Year	Day Type	Hour of Day					Average
		1 to 2 pm	2 to 3 pm	3 to 4 pm	4 to 5 pm	5 to 6 pm	
1-in-2	Typical Event Day	11.5	16.4	18.1	18.9	20.2	17.0
	May Monthly Peak	9.4	11.6	13.1	14.6	15.9	12.9
	June Monthly Peak	2.0	2.6	3.7	4.7	5.2	3.6
	July Monthly Peak	10.5	15.0	15.9	16.6	17.8	15.2
	August Monthly Peak	11.9	16.9	18.6	19.4	20.6	17.5
	September Monthly Peak	14.6	20.9	22.1	23.1	24.6	21.1
	October Monthly Peak	11.6	16.7	17.7	18.5	20.0	16.9
1-in-10	Typical Event Day	13.6	19.6	22.1	22.9	22.2	20.1
	May Monthly Peak	10.0	13.1	14.1	15.7	17.2	14.0
	June Monthly Peak	14.3	18.2	19.3	21.4	22.5	19.1
	July Monthly Peak	13.4	19.3	20.5	21.4	22.8	19.5
	August Monthly Peak	14.7	20.9	23.4	24.3	23.7	21.4
	September Monthly Peak	16.4	23.4	24.7	25.8	27.8	23.6
	October Monthly Peak	12.4	17.8	18.7	19.7	21.5	18.0

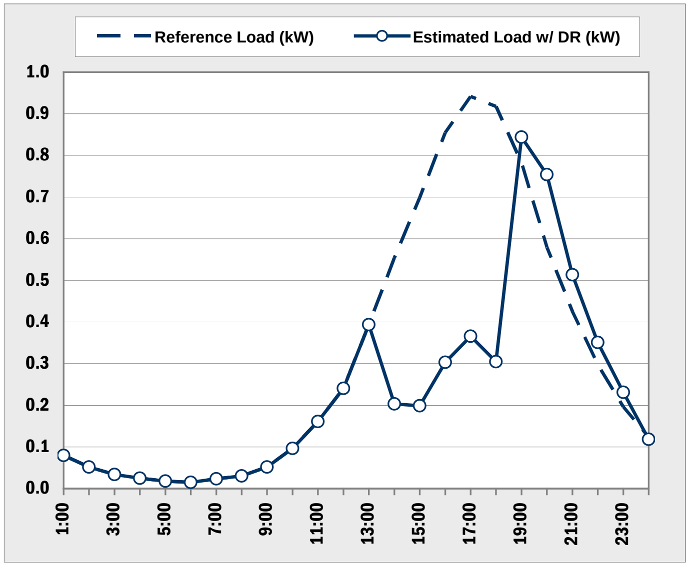
Figure 3-7
Hourly Load Impact Estimates for the Average Residential AC Unit
Typical Event Day, 1-in-2 Year Weather Conditions, 2012 Enrollment

TABLE 1: Menu options

Type of Results	Average AC Unit
Weather Year	1-in-2
Forecast Year	2012
Day Type	Typical Event Day
Customer Characteristic	All Residential Customers

TABLE 2: Output

Average Tons per AC Unit	3.5
Aggregate Tons	115,441
% Load Reduction (1 to 6 pm)	65.3%
Proxy Date	N/A



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
1:00	0.08	0.08	0.00	68.7	-0.01	-0.01	0.00	0.01	0.01
2:00	0.05	0.05	0.00	68.2	-0.01	-0.01	0.00	0.01	0.01
3:00	0.03	0.03	0.00	67.7	-0.01	-0.01	0.00	0.01	0.01
4:00	0.02	0.02	0.00	67.4	-0.01	-0.01	0.00	0.01	0.01
5:00	0.02	0.02	0.00	67.2	-0.01	-0.01	0.00	0.01	0.01
6:00	0.02	0.02	0.00	66.8	-0.01	-0.01	0.00	0.01	0.01
7:00	0.02	0.02	0.00	66.7	-0.01	-0.01	0.00	0.01	0.01
8:00	0.03	0.03	0.00	71.8	-0.01	-0.01	0.00	0.01	0.01
9:00	0.05	0.05	0.00	78.1	-0.01	-0.01	0.00	0.01	0.01
10:00	0.10	0.10	0.00	83.5	-0.01	-0.01	0.00	0.01	0.01
11:00	0.16	0.16	0.00	87.4	-0.01	-0.01	0.00	0.01	0.01
12:00	0.24	0.24	0.00	88.1	-0.01	-0.01	0.00	0.01	0.01
13:00	0.39	0.39	0.00	87.0	-0.01	-0.01	0.00	0.01	0.01
14:00	0.55	0.20	0.35	86.3	0.34	0.34	0.35	0.36	0.37
15:00	0.70	0.20	0.50	85.5	0.48	0.49	0.50	0.51	0.51
16:00	0.85	0.30	0.55	85.0	0.54	0.55	0.55	0.56	0.57
17:00	0.94	0.37	0.58	83.1	0.56	0.57	0.58	0.58	0.59
18:00	0.92	0.30	0.61	80.1	0.60	0.61	0.61	0.62	0.63
19:00	0.78	0.84	-0.06	76.9	-0.08	-0.07	-0.06	-0.06	-0.05
20:00	0.58	0.75	-0.17	73.8	-0.19	-0.18	-0.17	-0.17	-0.16
21:00	0.43	0.51	-0.09	71.9	-0.10	-0.09	-0.09	-0.08	-0.07
22:00	0.30	0.35	-0.05	70.9	-0.07	-0.06	-0.05	-0.05	-0.04
23:00	0.20	0.23	-0.03	69.7	-0.05	-0.04	-0.03	-0.03	-0.02
0:00	0.12	0.12	0.01	69.5	-0.01	0.00	0.01	0.01	0.02
	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
Daily	7.59	5.41	2.18	159.4	2.11	2.15	2.18	2.21	2.25

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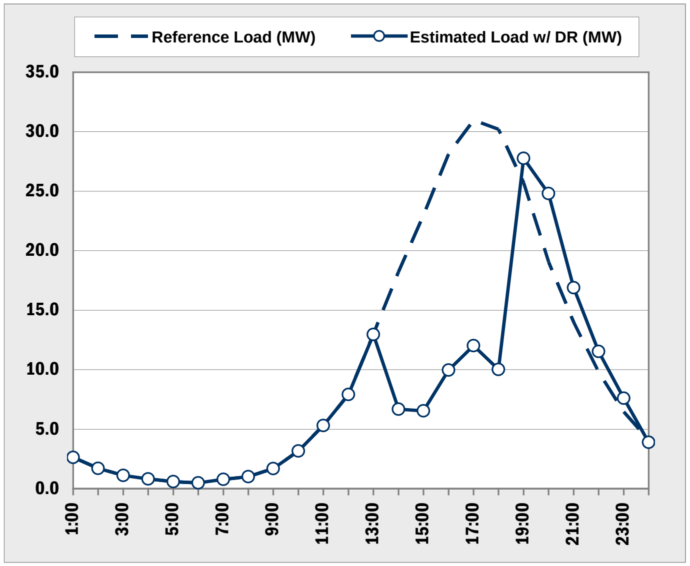
Figure 3-8
Hourly Load Impact Estimates for All Residential Customers Combined
Typical Event Day, 1-in-2 Year Weather Conditions, 2012 Enrollment\

TABLE 1: Menu options

Type of Results	Aggregate
Weather Year	1-in-2
Forecast Year	2012
Day Type	Typical Event Day
Customer Characteristic	All Residential Customers

TABLE 2: Output

Average Tons per AC Unit	3.5
Aggregate Tons	115,441
% Load Reduction (1 to 6 pm)	65.3%
Proxy Date	N/A



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
1:00	2.62	2.62	0.00	68.7	-0.49	-0.20	0.00	0.20	0.49
2:00	1.70	1.70	0.00	68.2	-0.49	-0.20	0.00	0.20	0.49
3:00	1.11	1.11	0.00	67.7	-0.49	-0.20	0.00	0.20	0.49
4:00	0.82	0.82	0.00	67.4	-0.49	-0.20	0.00	0.20	0.49
5:00	0.59	0.59	0.00	67.2	-0.49	-0.20	0.00	0.20	0.49
6:00	0.49	0.49	0.00	66.8	-0.49	-0.20	0.00	0.20	0.49
7:00	0.77	0.77	0.00	66.7	-0.49	-0.20	0.00	0.20	0.49
8:00	1.00	1.00	0.00	71.8	-0.49	-0.20	0.00	0.20	0.49
9:00	1.70	1.70	0.00	78.1	-0.49	-0.20	0.00	0.20	0.49
10:00	3.16	3.16	0.00	83.5	-0.49	-0.20	0.00	0.20	0.49
11:00	5.30	5.30	0.00	87.4	-0.49	-0.20	0.00	0.20	0.49
12:00	7.91	7.91	0.00	88.1	-0.49	-0.20	0.00	0.20	0.49
13:00	12.95	12.95	0.00	87.0	-0.49	-0.20	0.00	0.20	0.49
14:00	18.22	6.68	11.54	86.3	11.04	11.33	11.54	11.74	12.03
15:00	22.97	6.54	16.43	85.5	15.94	16.23	16.43	16.63	16.92
16:00	28.12	9.97	18.14	85.0	17.65	17.94	18.14	18.34	18.64
17:00	30.97	12.03	18.94	83.1	18.45	18.74	18.94	19.14	19.44
18:00	30.20	10.02	20.18	80.1	19.68	19.98	20.18	20.38	20.67
19:00	25.70	27.77	-2.07	76.9	-2.56	-2.27	-2.07	-1.87	-1.58
20:00	19.06	24.80	-5.74	73.8	-6.24	-5.95	-5.74	-5.54	-5.25
21:00	13.99	16.89	-2.91	71.9	-3.40	-3.11	-2.91	-2.71	-2.42
22:00	9.79	11.54	-1.75	70.9	-2.24	-1.95	-1.75	-1.55	-1.26
23:00	6.45	7.60	-1.15	69.7	-1.64	-1.35	-1.15	-0.94	-0.65
0:00	4.07	3.90	0.17	69.5	-0.32	-0.03	0.17	0.37	0.67
	Reference Energy Use (MWh)	Observed Energy Use (MWh)	Change in Energy Use (MWh)	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
Daily	249.67	177.88	71.78	159.4	69.37	70.79	71.78	72.77	74.19

3.4. Recommendations

Based on the analysis presented above, there are several findings that SDG&E should consider when conducting future impact evaluations and when marketing the Summer Saver program to new customers.

The comparison of load impact estimates based on whole building and end-use interval data indicates that accurate impact estimates for residential customers can be obtained from interval data collected at the premise level. Given this, once SDG&E has deployed a sufficient number of smart meters to allow a representative sample to be drawn from the residential Summer Saver participant population, SDG&E should seriously consider basing future evaluations on whole building data. This approach will be significantly less expensive and ultimately more accurate and robust, as it will allow for much larger sample sizes and more detailed analysis of how impacts vary across customer sub-segments.

Another important consideration for future evaluations is to recruit a subset of participants into a study group that is willing to be called more often than the standard event days that occur each season. For example, PG&E has recruited load research samples of customers from its air conditioning load program in the last several years that agree to have their air conditioners cycled 25 to 30 times across the summer based on a carefully designed operational plan that includes events of varying duration and cycling strategies on days with much wider variation in weather conditions than would occur naturally. One of the challenges in the evaluation presented here was that there was limited variation in temperatures across the estimating sample and very few operations occurred at the low and high end of the temperature spectrum. Given the non-linear nature of the relationship between weather and air conditioning use, it is difficult to confidently extrapolate from a model based on limited temperature variation to temperatures that are significantly above or below what occurred over the estimating sample. With a study group and sound operational plan involving more events operated across a wide range of weather conditions, better models could be developed that provide more accurate estimates for events on days with temperatures above 95 or even 100°F which, while rare, are exactly the days when events have the highest probability of occurring. Customers can be recruited into such study groups based on relatively modest incentives ($25 to $50). As such, SDG&E would be able to improve load impact estimates for much lower cost than has been required in the past once the cost of installing and maintaining an end-use load research sample has been eliminated because of the ability to provide accurate estimates based whole building level analysis using data from SDG&E's new smart meters.

Based on the load impacts and relatively simple cost-effectiveness calculations provided in Section 3.2.1, we suggest that SDG&E examine the relative incentives paid for two cycling options that customers can select. There is a clear selection bias that occurs in that customers with higher loads are more likely to select the lower cycling option, which in part explains the rather modest differential (about 30%) in the average load impacts between customers who select the 100% option compared with those on the 50% cycling option. This is significantly less than the payment differential for customers on these options, which is between 3 and 4 times higher depending on the common fixed cost for device installation and recruitment and the length of time over which the incentives are paid. A reduction in the incentives paid to the 100% cycling group combined with an increase in the incentives paid to the 50% cycling group could increase program enrollment while reducing costs and increasing cost-effectiveness. The lower incentive for the 100% cycling group might risk losing some participants, but the higher payment to the 50% cycling group would likely more than make up for this loss and could reduce program costs while possibly increasing aggregate load impacts.

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

4. COMMERCIAL SECTOR LOAD IMPACT ANALYSIS

This report section summarizes the ex post and ex ante load impacts for commercial customer participants in SDG&E's Summer Saver program. As previously discussed, the same seven event days were called for commercial participants as were called for residential program participants in 2009. Load reductions are reported for each ex post event and for the average event. Ex ante load impact estimates have been generated for each monthly system peak day based on both 1-in-2 and 1-in-10 year weather conditions for each forecast year from 2010 through 2020. Hourly estimates are provided in tables filed electronically in conjunction with this report. Selected summary values are contained in this chapter.

4.1. Analysis Methodology

The impact estimates for commercial customers were based on end use data. A model with whole building data was also estimated for comparison purposes. The end use analysis methodology is presented first and the whole house analysis methodology is discussed at the end of this section.

In total, 420 accounts were selected from SDG&E's full commercial participant population for the 2009 Summer Saver program evaluation. The sample design and selection process was discussed in Section 2. The final estimation was based on 250 individual air conditioning unit regressions.[11]

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

Table 4-1
Event Dates, Times, and Groups Called in Commercial Sample

Event Date	Start Time	End Time	Groups Called
7/21/2009	1:00 PM	5:00 PM	A and C
8/26/2009	1:00 PM	5:00 PM	B and C
8/27/2009	1:30 PM	5:30 PM	A and C
8/28/2009	1:30 PM	5:30 PM	B and C
9/2/2009	2:00 PM	6:00 PM	A and C
9/3/2009	2:00 PM	6:00 PM	B and C
9/24/2009	1:00 PM	5:00 PM	A and C

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

The explanatory variables in the commercial end use model are similar to those employed in the residential model, with a few exceptions. First, the commercial model includes five day types as opposed to two because commercial air conditioning load varies more throughout the week. Secondly, there are month and day type variables that are not interacted with CDD because commercial air conditioning units have substantial fan load that runs even when CDD is zero. Much like with a whole building model, variables that explain load that is not sensitive to weather need to be included. Finally, note that no night CDH variable was included as the commercial customers were not observed to be as responsive to heat buildup in the morning hours as their residential counterparts.

The commercial regressions were developed using the same GLS estimator and robust standard error techniques used for the residential analysis. The following equation summarizes the specification of the model used to estimate air conditioning load based on end use load data:

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

In this equation,

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

α_o = Estimated constant term;

β_{ij} through θ_m are the estimated coefficients;

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

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

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

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

CDD^2 = CDD squared

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

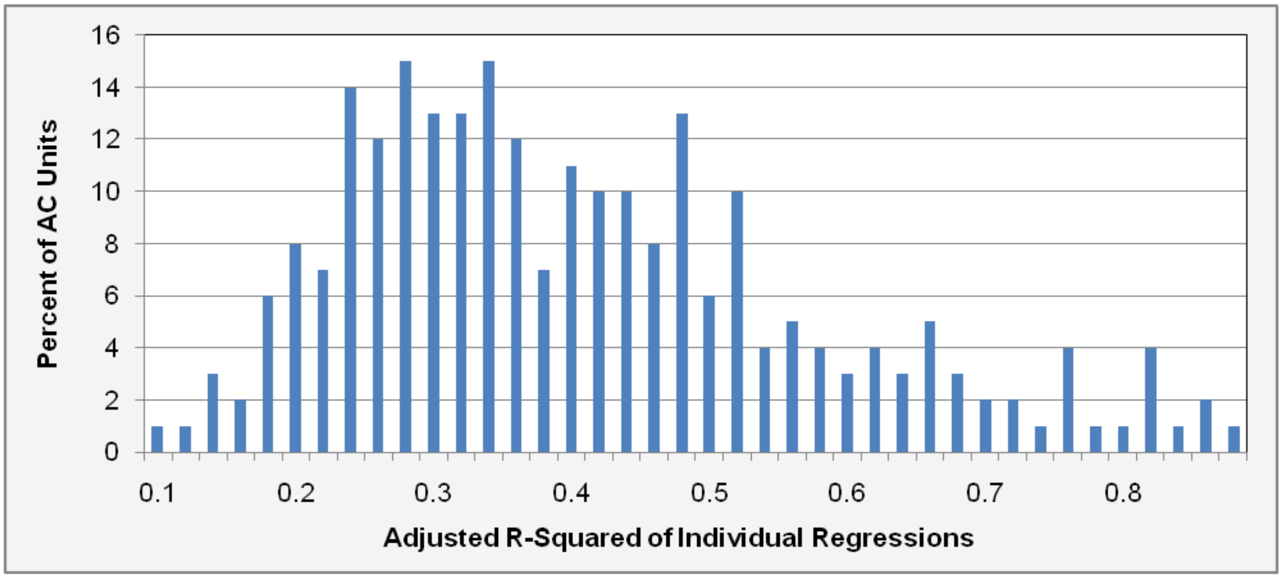
$POSTEVENTHOUR_m$= Series of binary variables representing twelve half-hour time periods immediately following the end of an event (1-12);

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

ε = the error term.

Figure 4-1 shows the distribution of R-squared values for the individual air conditioning unit regressions. Around one-third of individual regressions have R-squared values less than 0.3, whereas the upper one-third have R-squared values exceeding 0.45. Even though some of the individual R-squared values are low, the model explains nearly 97 percent of the variation in aggregate load when the predicted and actual values are aggregated by day and half-hour. Within each cycling strategy, the model also explains nearly 97 percent of aggregate load.

Figure 4-1
Distribution of R-squared Values from Individual Regressions based on Commercial End Use Load Data



As in the residential analysis, we can determine the accuracy of the reference load by comparing predicted and actual load for the comparison group on actual event days. Similarly, since participants in air conditioning load control programs do not shift load to pre-event hours, predicted and actual load for the curtailed group should match up closely in the hours leading up to the event.

Figure 4-2 compares the predicted and actual hourly air conditioning load of the comparison group for the average event day. The model predicts air conditioning load of the comparison group very well. The average error throughout the day is 3.8 percent. More importantly, the average error during the peak period from 1 to 6 pm is only 0.7 percent.

Figure 4-3 compares the predicted and actual hourly air conditioning load of the curtailed group for the average event day. The average error throughout the day is 2.8 percent and during event hours it is only 0.9 percent. Given that there are event and post-event variables in the model, it is expected that the model predicts well during those hours. In the hours leading up to the event, there are no event variables and the model performs well. From 6 am to 12 pm, the average error is 1.4 percent.

Figure 4-2
Predicted and Actual Commercial Air Conditioning Load for the Average Event Day
Comparison Group

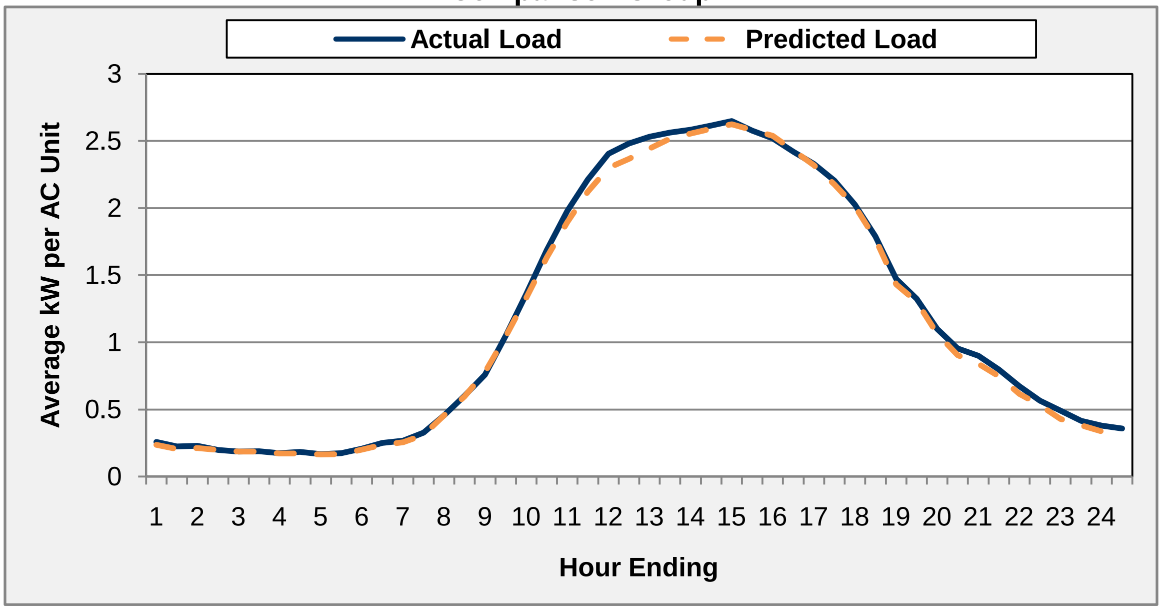


Figure 4-3
Predicted and Actual Commercial Air Conditioning Load for the Average Event Day
Curtailed Group

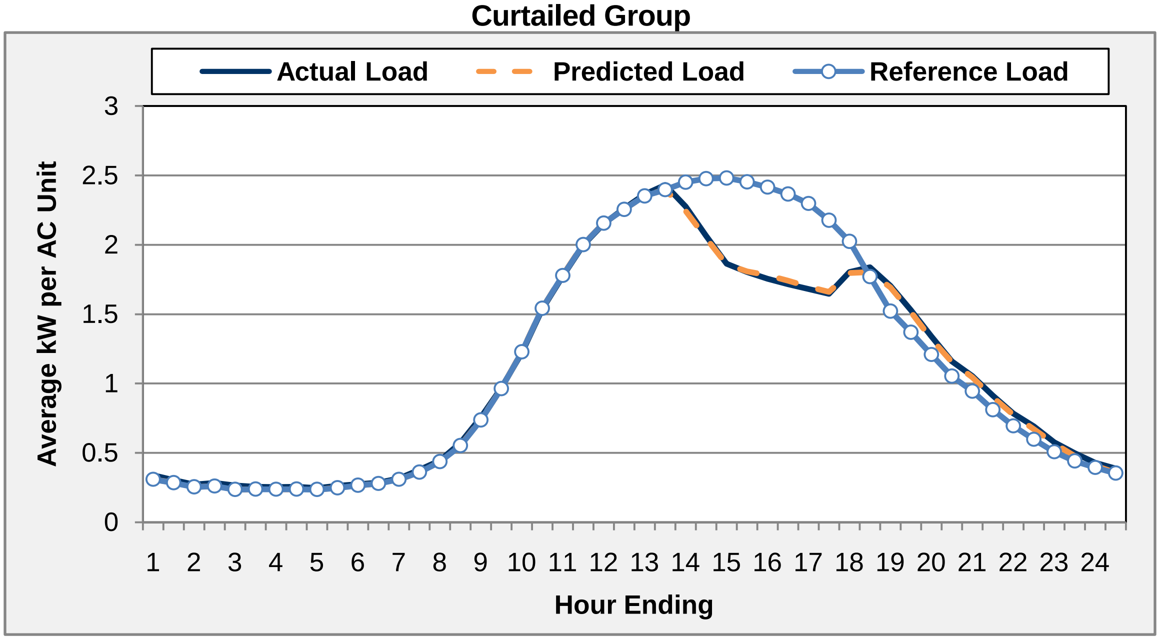
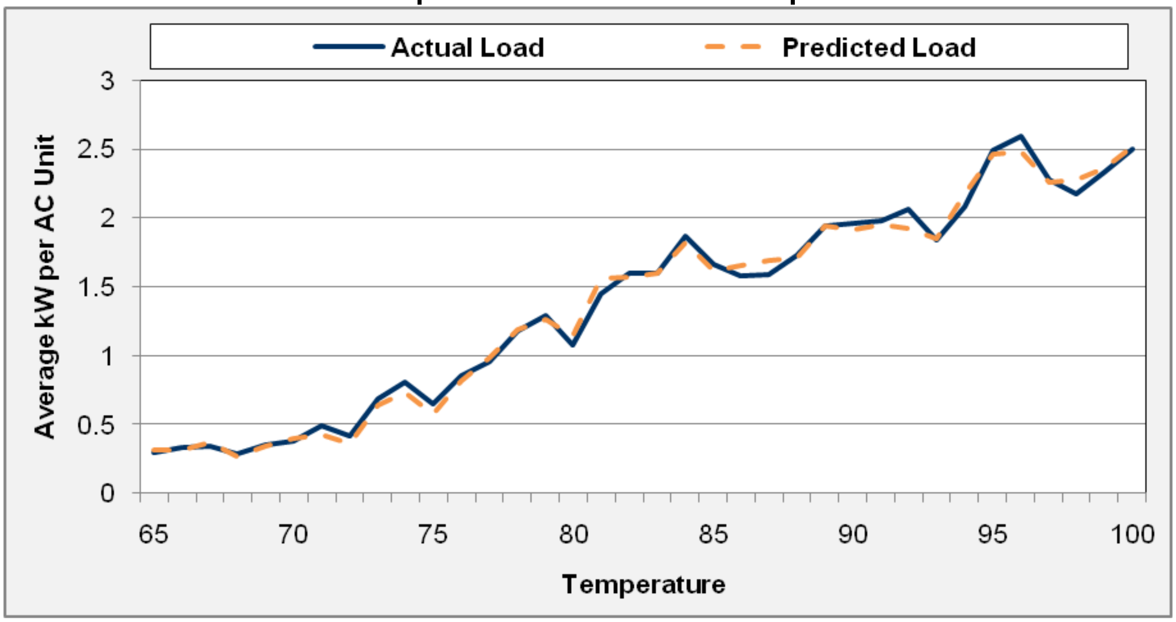


Figure 4-4 compares the predicted and actual air conditioning load by temperature on event days. This figure illustrates that the model predicts accurately across a range of temperatures. From 80 to 100 degrees, the average error is 2.9 percent.

Figure 4-4
Predicted and Actual Commercial Air Conditioning Load by Temperature on Event Days
Comparison and Curtailed Groups



The whole building model was nearly the same as the AC model except that CDD was interacted with month and half-hour instead of day type and half-hour. The whole building load impact estimates are compared to the AC estimates in Section 4.2.3. Although the final results are based on the AC model, it is important to see how well the whole building model predicts in order to understand why there are differences between the AC and whole building estimates.

Figure 4-5 compares the predicted and actual hourly whole building load of the comparison group for the average event day. Figure 4-6 compares the predicted and actual hourly whole building load of the curtailed group for the average event day. As shown in the figures, the whole building model also predicts well for the comparison and curtailed groups on event days.

Figure 4-5
Predicted and Actual Commercial Whole Building Load for the Average Event Day Comparison Group

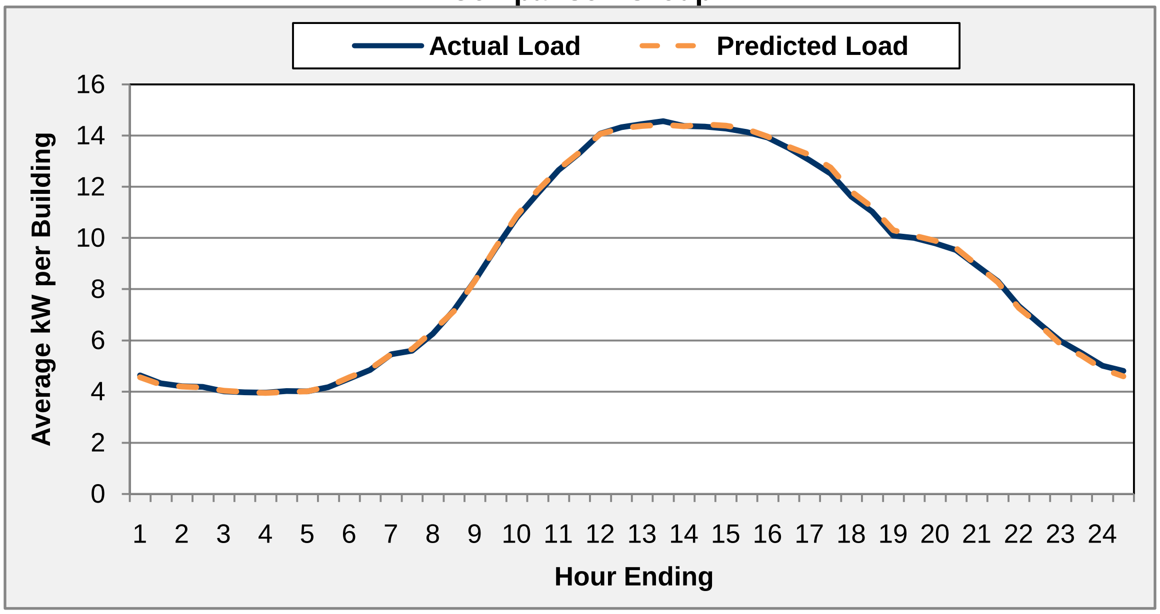
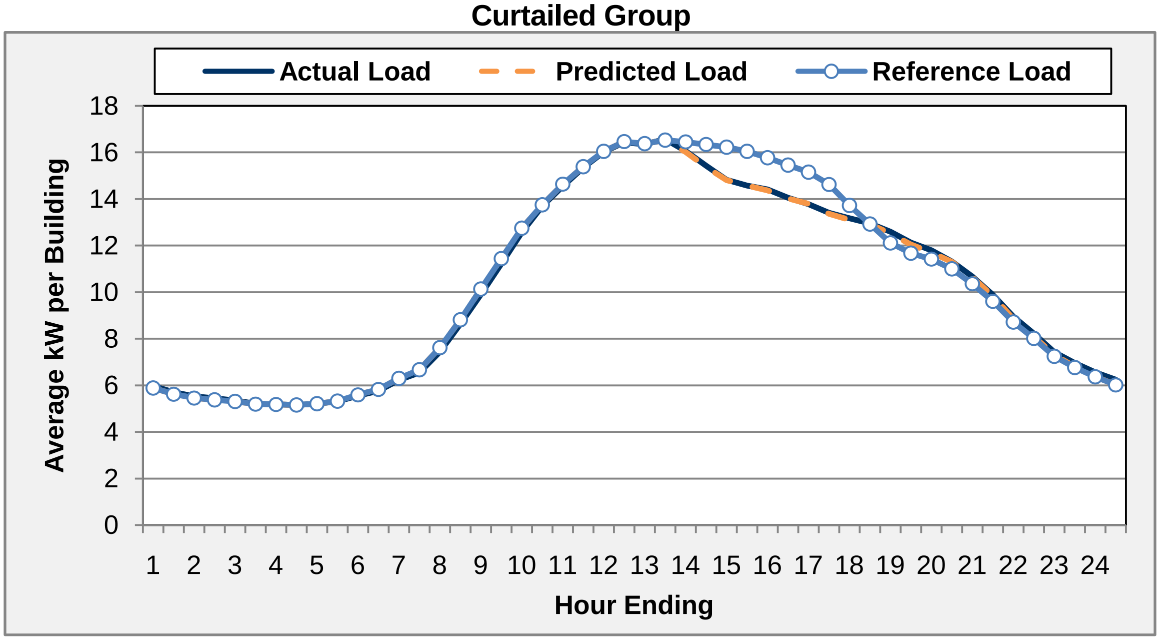


Figure 4-6
Predicted and Actual Commercial Whole Building Load for the Average Event Day Curtailed Group



4.2. Ex Post Load Impact Estimates

Tables 4-2 and 4-3 show the load impacts for each event, and for the average event, in 2009, for commercial Summer Saver participants. Table 4-2 reports the average values per customer and Table 4-3 reports the average values per ton of air conditioning. Each table shows enrollment on each event date, the reference load per customer or per ton, the average load with load control in effect, the average and percent load reduction, the aggregate load reduction and the average temperature. Recall from Section 2 that roughly 60% of commercial customers and 61% of the enrolled air conditioning tonnage selected the 50% cycling option over the 30% cycling option.

The average load reduction across the four-hour event window[12] and the seven events is 0.59 kW per air conditioning unit, or 0.14 kW per ton. The average reduction equaled roughly 25% of the typical reference load. The first and last events had the lowest average load reduction and were also the only stand alone events. The remaining events were called three days in a row in August and two days back-to-back in early September. The absolute average load reduction was highest on the second and third days of the August event sequence and on the second day of the two-day September sequence, suggesting that more air conditioning units were probably operating at higher duty cycles when system conditions warranted that events were called several days in a row.

The average aggregate load impact across the seven event days was 6.6 MW, and ranged from a low of 4.9 MW on July 21st to a high of 7.9 MW on August 27th. These aggregate estimates are based on program enrollment of approximately 5,400 commercial accounts and 48,471 tons of air conditioning. Enrollment changed very little over the course of the two months during which events were called in 2009, except for the small drop in September, which is not uncommon near the end of the summer.

Table 4-2
Average Hourly Load Reduction for Event Period by Event Day
All Commercial Customers, kW per AC Unit

Date	Day of Week	Enrolled Participants	Avg. Reference Load (kW)	Avg. Estimated Load w/ DR (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	5,313	2.23	1.79	0.44	19.9	4.9	83.0
8/26/2009	W	5,439	2.31	1.74	0.57	24.8	6.5	87.9
8/27/2009	Th	5,439	2.57	1.86	0.70	27.4	7.9	90.2
8/28/2009	F	5,439	2.41	1.73	0.68	28.1	7.6	89.6
9/2/2009	W	5,439	2.46	1.88	0.58	23.7	6.5	84.8
9/3/2009	Th	5,439	2.28	1.63	0.65	28.6	7.4	86.8
9/24/2009	Th	5,302	2.47	1.96	0.51	20.7	5.6	87.6
Average Event	**N/A**	**5,401**	**2.39**	**1.80**	**0.59**	**24.8**	**6.6**	**87.1**

[12] Recall from Section 2 that each event lasted four hours, but the event start time was either at 1 pm, 1:30 pm or 2 pm.

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

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

The average load impact per ton of air conditioning for commercial customers, 0.14 kW, is quite similar to the value for residential participants, which is 0.18 kW. However, the average reference load, normalized for tonnage, for commercial participants is two thirds higher than that of residential participants (0.55 kW/ton and 0.33 kW/ton, respectively). That is, commercial customer air conditioners run at much higher average duty cycles during the relevant hours than do residential customer air conditioners. This is not surprising, given the much higher occupancy rate of commercial establishments compared with households, and the larger internal lighting and other loads in many businesses. It is also true that fan loads run much more often when air conditioner compressors are not operating to support air circulation in businesses. All of these factors help explain why reference loads are higher on a per ton basis in commercial premises than in residential premises. The reason load impacts are lower than residential load impacts has to do, in part, with the lower cycling strategies offered to commercial participants (30% and 50% compared with 50% and 100% for residential customers). The fact that fan load, which is not shut down when cycling occurs, is a greater share of total electricity use for commercial customers, also contributes to the lower percent load reduction for commercial participants compared with residential participants.

Table 4-4 shows the load impacts delineated by cycling option. As was true for residential customers, a significant selection bias can be observed in that commercial customers who chose the 30% cycling option have average reference loads that are roughly 45% greater than for customers who chose the 50% cycling option. As a result of this selection bias, even though the percent load reduction for 30% cycling customers is roughly half that of the 50% cycling group, their average load impact, at 0.68 kW per air conditioning unit, is only about 18% less than for the 50% cycling group. These differentials are more in line with the differential incentives paid to the 30% and 50% cycling customers than was true for residential customers, where the 100% cycling customers received incentive payments that were roughly four times greater than for the 50% cycling group. For commercial customers, the incentive payment to the 50% cycling group is only about 67% higher than for the 30% cycling group, which is reasonably well aligned with the differential load reductions of the two groups.

Table 4-4
Average Hourly Load Reduction for Event Period by Cycling Option
(2009 Ex Post Load Impacts for Commercial Program Participants)

Cycling Strategy	Avg. Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Hourly Load Reduction (MW)
30% Cycling	19,095	0.72	0.57	0.15	21.2	2.9
50% Cycling	29,376	0.44	0.31	0.13	28.5	3.7
All Commercial	**48,471**	**0.55**	**0.41**	**0.14**	**24.8**	**6.6**

4.2.1. Distribution of Load Impacts

Table 4-5 shows the percent of participants who provide load reductions that exceed selected thresholds. Approximately 28% of participants provided no measureable load reduction during the seven events that were called in 2009, which is similar to the share of residential customers with no load impacts reported in Section 3. This result is somewhat surprising in that the overall reference load is much higher for commercial customers than it is for residential customers, on a per ton basis, suggesting that more customers are running their air conditioners more often. However, it must be kept in mind that the cycling strategies are much lower for commercial customers than for residential customers. In addition, a much greater share of commercial participants are located in the milder coastal climate zone (48% of commercial customers compared with only 13% of residential customers), where fan load is likely to be a much greater share of total air conditioning electricity use, thus increasing the likelihood that a given commercial customer will provide limited load impacts even though stores are always occupied.

Table 4-5
Share of Commercial Customers Exceeding Load Reduction per Ton Thresholds by Cycling Option

Customer Category	Share of Accounts (%) Providing Load Reductions Greater Than:					
	0.0 kW/Ton	0.1 kW/Ton	0.2 kW/Ton	0.3 kW/Ton	0.4 kW/Ton	0.5 kW/Ton
Commercial - 30% Cycling	75.8	56.2	39.9	24.7	10.8	8.4
Commercial - 50% Cycling	69.3	41.1	33.8	25.6	18.5	12.0
All Commercial Customers	**71.8**	**47.0**	**36.1**	**25.2**	**15.5**	**10.6**

In an effort to determine whether low and high responders can be identified and either avoided or targeted in future marketing efforts, an analysis of the distribution of impacts by business type was made. Table 4-6 shows the distribution of load impacts provided by customers stratified by five business types - Religious Institutions; Restaurants; Retail Stores; Offices, Hotels, Finance, Service (OHFS); and Other. These are not the conventional segments used because Summer Saver shows an unconventional distribution of tons by business type. Religious Institutions account for around 10,000 tons of air conditioning in the program, which is roughly 21% of the total commercial tons. Customers in the OHFS and Other segments each account for around 27% of the total commercial tons. Restaurants account for approximately 10% and Retail Stores account for the remaining 15%. All of these segments are well represented in the sample, so the table provides robust estimates of the distribution of impacts by industry.

Only 8.3% of customers in the Retail segment provided no load reduction over the seven events in 2009, whereas 45.4% of customers in the Religious Institutions segment and 34% in the Restaurant segment provided no demand response. At the other end of the spectrum, few customers in the Religious Institutions segment provided load reductions exceeding 0.5 kW/ton, whereas around 15% of customers in the Retail and OHFS segments provided load reductions exceeding this threshold.

Table 4-6
Share of Commercial Customers Exceeding Load Reduction per Ton Thresholds by Selected Industries

Industry	Share of Accounts (%) Providing Load Reductions Greater Than:					
	0.0 kW/Ton	0.1 kW/Ton	0.2 kW/Ton	0.3 kW/Ton	0.4 kW/Ton	0.5 kW/Ton
Religious Institutions	54.6	22.7	8.9	5.2	5.2	5.2
Restaurants	66.0	38.1	27.8	22.7	15.6	9.7
Retail stores	91.7	68.6	56.6	43.6	24.2	14.8
Offices, Hotels, Finance, Services	71.7	53.2	46.8	32.1	20.1	14.1
Other	75.4	51.8	40.8	24.8	14.3	9.7
All Commercial Customers	**71.8**	**47.0**	**36.1**	**25.2**	**15.5**	**10.6**

4.2.2. Load Impacts by Business Type

Table 4-7 shows how load impacts vary across the business types that are usually reported. The three business types that have the largest share of enrolled participants, enrolled air conditioning tons and aggregate impacts are, in order, the OHFS segment, the Institutional-Government segment and the Retail segment. The OHFS segment, which includes the Restaurant segment in this table, accounts for 44% of enrolled participants, 36% of enrolled tonnage and 39% of the aggregate load reduction. The Institutional-Government segment accounts for 18%, 28% and 11% of those values, respectively and Retail stores account for 18%, 14% and 29% of those values. The segment with the highest load reduction per ton of air conditioning is the Retail segment and the segment with the lowest reference load and average load impact is the Institutional-Government segment, which includes Religious Institutions. There is less variation in the percent load reduction across segments, ranging from a low of 18.7% to a high of 36.4%, than there is in the absolute load reduction, which varies by greater than a factor of five, from a low of 0.05 kW/ton for Institutional-Government to a high of 0.27 kW/ton for the Retail segment.

Table 4-7
Summer Saver Load Impacts by Business Type

Industry	Avg. Enrolled Participants	Avg. Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Estimated Load w/ DR (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Hourly Load Reduction (MW)
Ag., Min & Cons.	205	1,701	0.37	0.24	0.14	36.4	0.2
Manufacturing	330	2,710	0.71	0.53	0.17	24.6	0.5
Wh., Tr. & Oth. Util.	280	2,149	0.95	0.72	0.23	23.9	0.5
Retail Stores	957	6,793	0.88	0.60	0.27	31.2	1.9
Off., Hot., Fin. & Serv.	2,378	17,705	0.63	0.48	0.15	23.2	2.6
Schools	110	3,028	0.53	0.43	0.10	18.7	0.3
Institutional/Gov.	961	13,349	0.27	0.22	0.05	19.5	0.7
All Customers	**5,401**	**48,471**	**0.55**	**0.41**	**0.14**	**24.8**	**6.6**

4.2.3. Comparison of End Use and Whole Building Load Impact Estimates

An important consideration for future program evaluations is whether load impacts can be accurately estimated using load data for the entire commercial premise rather than using the end-use data that underlie the load impacts presented here. As noted in Section 3.2.4, obtaining end use air conditioning load data is expensive as it requires paying a representative sample of customers to allow data loggers or dual socket meters to be installed, installing the equipment and retrieving the data at the end of the program season. If accurate load estimates could be obtained from whole building data, once all of SDG&E's smart meters are installed, it would be possible to estimate load impacts based on a much larger and potentially more representative sample of customers at much lower cost than can be done through end use data collection.

Table 4-8 contains estimates of load impacts for the average commercial participant as well as for the average participant in each of the two cycling groups based on end use and whole building data. As seen, the estimates based on the whole building data are systematically lower than those obtained from the end-use data for the two groups combined, as well as for each cycling group. For the 50% cycling group and the two cycling groups combined, the average impact across the seven event days based on the whole building data analysis is approximately 15% lower than the average impact estimate based on the end-use data. For the 30% cycling group, the load impact estimate based on whole building data is more than 40% less than the estimate based on end use data. The primary reason that the comparisons for the 30% cycling group are not as close as for the other two comparison groups is that the "signal to noise" ratio is lower for those on 30% cycling than for those on 50% cycling. By this, we mean that the magnitude of the impact of air conditioner cycling (the signal) is smaller when 30% cycling is used relative to the variation in load across hours than it is when 50% cycling is used and, therefore, is more difficult to isolate using regression analysis than when the impact is larger.

It is difficult to understand why there is a systematic, downward bias in the estimates based on whole building data compared with those based on end-use data. As was seen in Figures 4-2 through 4-6, the reference load and load impact models appear to perform very well based on both the end-use and whole building data. In light of these findings, we recommend that SDG&E continue to base impact estimates on end-use data but also to continue studying the issue with additional data and analysis to determine whether different model specifications, more event day data, larger samples or some other adjustments might indicate that using whole building data to estimate load impacts for commercial customers is prudent.

Table 4-8
Comparison of Residential Load Impact Estimates Based on End-Use and Whole Building Data (Unweighted data)[13]

Event Date	Both Groups		30% Cycling Group		50% Cycling Group	
	AC Impact (kW/Ton)	WB Impact (kW/Ton)	AC Impact (kW/Ton)	WB Impact (kW/Ton)	AC Impact (kW/Ton)	WB Impact (kW/Ton)
7/21/2009	0.11	0.10	0.12	0.11	0.11	0.10
8/26/2009	0.15	0.12	0.18	0.11	0.14	0.13
8/27/2009	0.18	0.15	0.19	0.15	0.18	0.15
8/28/2009	0.18	0.14	0.21	0.13	0.17	0.15
9/2/2009	0.15	0.13	0.16	0.13	0.15	0.12
9/3/2009	0.18	0.14	0.20	0.12	0.16	0.14
9/24/2009	0.13	0.11	0.14	0.12	0.12	0.11
Average Event	0.15	0.13	0.17	0.12	0.15	0.13

4.3. Ex Ante Load Impact Estimates

The models developed from the ex post load data in 2009 were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2010 through 2020. SDG&E provided enrollment estimates by customer type and cycling option, which were presented in Table 2-2. As indicated in Section 2, the program is forecasted to reach a steady state by the end of 2011, with future enrollment equal to attrition. As such, the last year in which load impact estimates change is 2012. Ex ante estimates for 2013 through 2020 are the same as for 2012. The ex ante event window chosen by SDG&E is from 1 to 6 pm.[14]

Table 4-9 summarizes the average load impact across the five hour event window for each monthly system peak day and the typical event day, under 1-in-2 and 1-in-10 year weather conditions based on the steady state enrollment levels reached by the beginning of 2012. Load impact estimates are presented for the average air conditioning unit, for each ton of air conditioning and for all commercial participants as a whole. For a typical event based on 1-in-2 year weather conditions, the average reduction per air conditioning unit for commercial program participants is 0.46 kW, and the average reduction per ton of air conditioning is 0.11 kW. Based on 1-in-10 year weather conditions, these values are roughly 25% higher. The aggregate program load reduction potential provided by commercial participants is 5.7 MW for a typical event

[13] The values in each cell of this table would change if the data were weighted, but the differences would be the same on a percentage basis and the conclusions would also be the same. Values in this table should not be compared with those in Table 4-2, which are based on weighted estimates.

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

under 1-in-2 year weather conditions, and 7.2 MW under 1-in-10 year weather conditions. These values are based on program enrollment equal to 53,631 tons of air conditioning.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather conditions, the very low temperature in June produces very small average and aggregate load impact estimates. The June value is around 70% lower than the September estimate, which is the highest of any month. Based on 1-in-10 year weather conditions, the June value is more than three times higher than the 1-in-2 year June value. The weather conditions on the monthly system peak day in May produce the lowest value based on 1-in-10 year weather, followed by October. The highest load impacts are in September in the 1-in-10 weather year, with the system peak estimate equaling 8.3 MW.

Table 4-9
Average and Aggregate Load Reductions by Day Type and Weather Year
All Commercial Customers
Forecast Year 2012

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

Table 4-10 shows the aggregate load impacts for each month over the three year period from 2010 through 2012. Both commercial customer enrollment and aggregate load impacts grow by roughly 10% over the forecast period.

Table 4-10
Aggregate Load Reductions by Day Type, Weather Year and Forecast Year
All Commercial Customers

Forecast Year	Day Type	Projected Tons	Aggregate Load Reduction (MW)	
			1-in-2 Year	1-in-10 Year
2010	Typical Event Day	48,800	5.2	6.5
	May Monthly Peak	47,592	3.9	4.6
	June Monthly Peak	47,994	1.7	5.8
	July Monthly Peak	48,397	4.8	5.8
	August Monthly Peak	48,800	5.3	6.8
	September Monthly Peak	49,202	6.5	7.6
	October Monthly Peak	49,605	4.9	5.6
2011	Typical Event Day	52,624	5.6	7.0
	May Monthly Peak	52,020	4.2	5.0
	June Monthly Peak	52,222	1.9	6.3
	July Monthly Peak	52,423	5.2	6.3
	August Monthly Peak	52,624	5.7	7.3
	September Monthly Peak	52,826	7.0	8.2
	October Monthly Peak	53,027	5.2	6.0
2012 to 2020	Typical Event Day	53,631	5.7	7.2
	May Monthly Peak	53,631	4.3	5.2
	June Monthly Peak	53,631	1.9	6.5
	July Monthly Peak	53,631	5.3	6.4
	August Monthly Peak	53,631	5.8	7.4
	September Monthly Peak	53,631	7.1	8.3
	October Monthly Peak	53,631	5.3	6.1

4.3.1. Load Impacts by Hour

Figures 4-5 and 4-6 contain the standard output tables required by the CPUC Load Impact Protocols for the average commercial customer and for all commercial customers combined for the typical event day based on 1-in-2 year weather conditions and 2012 enrollment. Electronic versions of these tables for various day types and weather conditions have been filed along with this report.

Table 4-11 shows how load impacts vary across the five-hour event window for each required ex ante day type and set of weather conditions based on 2012 enrollment. There is some variation in load impacts across event hours, monthly system peak days and weather conditions, although the variation across hours is not as great as was seen for residential customers.

Unlike for residential customers, where the lowest load impacts were seen in the first event hour and the highest were seen in the last event hour, for commercial customers, the pattern is quite different. Indeed, for all monthly system peak days under both sets of weather conditions, the lowest impact is seen in the last hour of the five-hour event window, from 5 to 6 pm. The load impact in this hour is about 20% less than the average across the five hours, and is around 25% lower than the peak hour. In every instance, the peak load reduction occurs between 2 and 3 pm.

Table 4-11
Aggregate Load Reductions by Day Type, Weather Year and Hour
All Commercial Customers, 2012 Enrollment

Weather Year	Day Type	Hour of Day					Average
		1 to 2 pm	2 to 3 pm	3 to 4 pm	4 to 5 pm	5 to 6 pm	
1-in-2	Typical Event Day	5.8	6.1	6.1	5.9	4.7	5.7
	May Monthly Peak	4.4	4.7	4.6	4.5	3.5	4.3
	June Monthly Peak	2.0	2.0	2.0	2.0	1.6	1.9
	July Monthly Peak	5.4	5.7	5.6	5.4	4.3	5.3
	August Monthly Peak	5.9	6.2	6.2	6.0	4.7	5.8
	September Monthly Peak	7.2	7.6	7.5	7.3	5.8	7.1
	October Monthly Peak	5.3	5.7	5.6	5.5	4.3	5.3
1-in-10	Typical Event Day	7.3	7.7	7.6	7.4	5.8	7.2
	May Monthly Peak	5.2	5.6	5.5	5.3	4.2	5.2
	June Monthly Peak	6.5	6.9	6.9	6.7	5.3	6.5
	July Monthly Peak	6.5	6.9	6.8	6.6	5.2	6.4
	August Monthly Peak	7.5	8.0	7.9	7.7	6.0	7.4
	September Monthly Peak	8.4	8.9	8.8	8.5	6.7	8.3
	October Monthly Peak	6.1	6.6	6.5	6.3	4.9	6.1

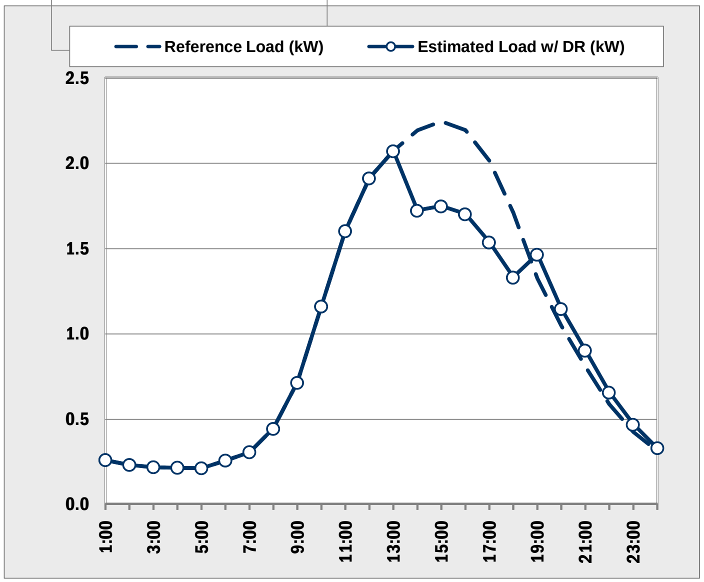
Figure 4-7
Hourly Load Impact Estimates for the Average Commercial AC Unit
Typical Event Day, 1-in-2 Year Weather Conditions, 2012 Enrollment

TABLE 1: Menu options

Type of Results	Average AC Unit
Weather Year	1-in-2
Forecast Year	2012
Day Type	Typical Event Day
Customer Characteristic	All Commercial Customers

TABLE 2: Output

Average Tons per AC Unit	4.3
Aggregate Tons	53,631
% Load Reduction (1 to 6 pm)	22.3%
Proxy Date	N/A



Hour Ending	Reference Load (kW)	Estimated Load w/ DR (kW)	Load Impact (kW)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
1:00	0.26	0.26	0.00	69.1	-0.03	-0.01	0.00	0.01	0.03
2:00	0.23	0.23	0.00	68.6	-0.03	-0.01	0.00	0.01	0.03
3:00	0.22	0.22	0.00	68.1	-0.03	-0.01	0.00	0.01	0.03
4:00	0.21	0.21	0.00	67.7	-0.03	-0.01	0.00	0.01	0.03
5:00	0.21	0.21	0.00	67.5	-0.03	-0.01	0.00	0.01	0.03
6:00	0.25	0.25	0.00	67.2	-0.03	-0.01	0.00	0.01	0.03
7:00	0.30	0.30	0.00	67.3	-0.03	-0.01	0.00	0.01	0.03
8:00	0.44	0.44	0.00	71.3	-0.03	-0.01	0.00	0.01	0.03
9:00	0.71	0.71	0.00	76.7	-0.03	-0.01	0.00	0.01	0.03
10:00	1.16	1.16	0.00	81.4	-0.03	-0.01	0.00	0.01	0.03
11:00	1.60	1.60	0.00	84.9	-0.03	-0.01	0.00	0.01	0.03
12:00	1.91	1.91	0.00	85.3	-0.03	-0.01	0.00	0.01	0.03
13:00	2.07	2.07	0.00	84.5	-0.03	-0.01	0.00	0.01	0.03
14:00	2.19	1.72	0.47	84.0	0.44	0.46	0.47	0.48	0.50
15:00	2.24	1.75	0.50	83.5	0.47	0.48	0.50	0.51	0.53
16:00	2.19	1.70	0.49	83.0	0.46	0.48	0.49	0.50	0.52
17:00	2.01	1.54	0.48	81.4	0.45	0.46	0.48	0.49	0.51
18:00	1.71	1.33	0.38	78.7	0.35	0.37	0.38	0.39	0.41
19:00	1.32	1.46	-0.14	76.2	-0.17	-0.16	-0.14	-0.13	-0.11
20:00	1.04	1.15	-0.10	73.6	-0.13	-0.11	-0.10	-0.09	-0.07
21:00	0.81	0.90	-0.10	71.9	-0.13	-0.11	-0.10	-0.08	-0.07
22:00	0.58	0.66	-0.07	71.1	-0.10	-0.08	-0.07	-0.06	-0.04
23:00	0.42	0.47	-0.05	70.1	-0.08	-0.06	-0.05	-0.03	-0.02
0:00	0.31	0.33	-0.02	69.7	-0.05	-0.03	-0.02	0.00	0.01

	Reference Energy Use (kWh)	Observed Energy Use (kWh)	Change in Energy Use (kWh)	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
					10th	30th	50th	70th	90th
Daily	24.42	22.58	1.84	137.5	1.69	1.78	1.84	1.90	1.98

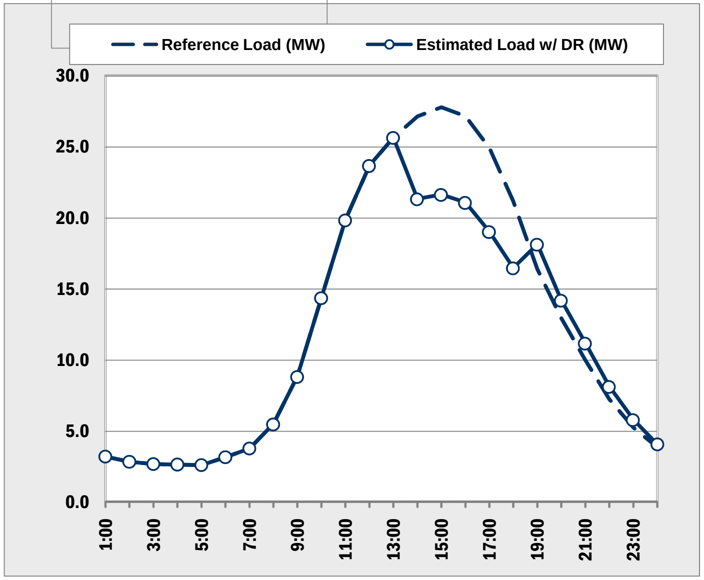
Figure 4-8
Hourly Load Impact Estimates for All Commercial Customers Combined
Typical Event Day, 1-in-2 Year Weather Conditions, 2012 Enrollment

TABLE 1: Menu options

Type of Results	Aggregate
Weather Year	1-in-2
Forecast Year	2012
Day Type	Typical Event Day
Customer Characteristic	All Commercial Customers

TABLE 2: Output

Average Tons per AC Unit	**4.3**
Aggregate Tons	**53,631**
% Load Reduction (1 to 6 pm)	**22.3%**
Proxy Date	**N/A**



Hour Ending	Reference Load (MW)	Estimated Load w/ DR (MW)	Load Impact (MW)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
					10th	**30th**	**50th**	**70th**	**90th**
1:00	3.18	3.18	0.00	69.1	-0.37	-0.15	0.00	0.15	0.37
2:00	2.82	2.82	0.00	68.6	-0.37	-0.15	0.00	0.15	0.37
3:00	2.66	2.66	0.00	68.1	-0.37	-0.15	0.00	0.15	0.37
4:00	2.63	2.63	0.00	67.7	-0.37	-0.15	0.00	0.15	0.37
5:00	2.59	2.59	0.00	67.5	-0.37	-0.15	0.00	0.15	0.37
6:00	3.14	3.14	0.00	67.2	-0.37	-0.15	0.00	0.15	0.37
7:00	3.75	3.75	0.00	67.3	-0.37	-0.15	0.00	0.15	0.37
8:00	5.49	5.49	0.00	71.3	-0.37	-0.15	0.00	0.15	0.37
9:00	8.83	8.83	0.00	76.7	-0.37	-0.15	0.00	0.15	0.37
10:00	14.37	14.37	0.00	81.4	-0.37	-0.15	0.00	0.15	0.37
11:00	19.84	19.84	0.00	84.9	-0.37	-0.15	0.00	0.15	0.37
12:00	23.66	23.66	0.00	85.3	-0.37	-0.15	0.00	0.15	0.37
13:00	25.64	25.64	0.00	84.5	-0.37	-0.15	0.00	0.15	0.37
14:00	27.13	21.32	5.81	84.0	5.44	5.66	5.81	5.96	6.19
15:00	27.77	21.63	6.14	83.5	5.77	5.99	6.14	6.30	6.52
16:00	27.15	21.07	6.08	83.0	5.70	5.92	6.08	6.23	6.45
17:00	24.92	19.02	5.90	81.4	5.53	5.75	5.90	6.06	6.28
18:00	21.16	16.47	4.69	78.7	4.32	4.54	4.69	4.84	5.06
19:00	16.37	18.13	-1.77	76.2	-2.14	-1.92	-1.77	-1.61	-1.39
20:00	12.94	14.19	-1.26	73.6	-1.63	-1.41	-1.26	-1.10	-0.88
21:00	9.97	11.17	-1.20	71.9	-1.57	-1.35	-1.20	-1.05	-0.83
22:00	7.23	8.13	-0.89	71.1	-1.27	-1.05	-0.89	-0.74	-0.52
23:00	5.23	5.80	-0.57	70.1	-0.94	-0.72	-0.57	-0.41	-0.19
0:00	3.84	4.04	-0.20	69.7	-0.58	-0.35	-0.20	-0.05	0.17

	Reference Energy Use (MWh)	Observed Energy Use (MWh)	Change in Energy Use (MWh)	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
					10th	**30th**	**50th**	**70th**	**90th**
Daily	302.31	279.57	22.74	137.5	20.91	21.99	22.74	23.49	24.57

4.4. Recommendations

Our primary recommendation for future evaluations is to continue to explore whether load impact estimates based on whole building data can be used in place of end use data.. We believe SDG&E should install an end use load research sample in 2010. Importantly, special attention should be placed on accurately aligning the air conditioning tonnage data with the end use logger data and the whole building data when selecting and deploying the sample. In developing the sampling strategy, we believe that it is important to randomly select an air conditioning unit when multiple units are present, so that it is possible to compare in aggregate the whole building and end use estimates for a random sample of customers even though the number of controlled units associated with the whole building data may be greater than the number of units for which end use data are available. As discussed in the recommendations section for residential customers, we also believe that SDG&E should consider paying customers to allow for additional events to be called in order to improve load impact estimates.

Finally, SDG&E should consider using NAICS codes to target customers that are high responders and avoid customers that are low responders. Customers in the Religious Institutions (NAICS code beginning with 813) and Restaurant segments (NAICS code beginning with 722) have a much higher percentage of free riders compared with other segments. Customers in the Retail Stores segment (NAICS code beginning with 44 or 45) should be targeted. Business type is a strong driver of load impacts and can be used to identify and recruit customers who will increase the average load reduction among program participants.

5. AGGREGATE LOAD IMPACT ANALYSIS

This report section provides a brief summary of the load impacts for the entire Summer Saver program. It combines the load impacts for residential and commercial customers that were presented in prior sections.

5.1. Ex Post Load Impacts

Tables 5-1 and 5-2 show the ex post load impact estimates for the program as a whole. Table 5-1 contains average estimates per participant, and Table 5-2 presents averages in terms of tons of air conditioning load. In total, the Summer Saver program delivered an average load reduction across the four-hour event window and the seven event days equal to 23.6 MW. The impacts ranged from a low of 17.4 MW on July 21st to a high of 27.7 MW on August 27th. The percent load reduction also varied across events, from a low of 35% on September 2nd to a high of 46% on August 28th.

Table 5-1
Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Participants, kW per AC Unit

Date	Day of Week	Enrolled Participants	Avg. Reference Load (kW)	Avg. Estimated Load w/ DR (kW)	Avg. Load Reduction (kW)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/21/2009	Tu	28,510	1.33	0.86	0.47	35.1	17.4	84.5
8/26/2009	W	29,504	1.43	0.82	0.61	42.7	23.1	89.7
8/27/2009	Th	29,504	1.74	1.02	0.72	41.2	27.7	92.0
8/28/2009	F	29,504	1.56	0.84	0.72	46.2	27.3	91.5
9/2/2009	W	29,503	1.70	1.11	0.59	34.8	22.8	85.8
9/3/2009	Th	29,503	1.63	0.96	0.68	41.6	25.7	87.8
9/24/2009	Th	29,413	1.55	1.01	0.55	35.3	21.1	89.4
Average Event	**N/A**	**29,349**	**1.56**	**0.94**	**0.62**	**39.6**	**23.6**	**88.7**

Table 5-2
2009 Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Customers, kW per Ton of Air Conditioning

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

5.2. Ex Ante Load Impacts

Table 5-3 shows the estimated ex ante load impacts for each monthly peak day and set of weather conditions. For a typical event day and 1-in-2 year weather conditions, aggregate load impacts are estimated equal 22.8 MW. The estimate for a typical event day under 1-in-10 year conditions is 19% higher. On the highest peak day for 1-in-2 year weather conditions, the load reduction is estimated to equal 28.2 MW. With the more extreme 1-in-10 year conditions, the estimated impact is 31.9 MW.

Table 5-3
Estimated Ex Ante Load Impacts for the Summer Saver Program in 2012

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