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2010 Load Impact Evaluation of San Diego Gas & Electric Company's Summer Saver Program

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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 2010 and ex ante load impact forecasts for 2011 through 2021.

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

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 the end of 2010, there were 32,000 premises enrolled in the program, which in aggregate have 162,000 tons of air conditioning capacity. About 80% of participants were residential customers, who account for 65% of the total tons of cooling that are subject to control under the program. Roughly 50% of residential participants are on the 100% cycling option. Almost 60% of commercial customers selected the 50% cycling option over the 30% option. Summer Saver enrollment is expected to stay roughly the same for the foreseeable future.

1.1 Ex Post Load Impact Estimates

Eleven Summer Saver events were called in 2010. All events were four hours long and each one began at either 1 PM or 2 PM. The first event was on July 15th. Two events were called in July, six in August, and three in September, with the last event occurring on September 29th. All of the events were called in groups: the two July events were successive, the August events were called in two groups of three days each in consecutive weeks and 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. Summer Saver residential customers delivered an average aggregate load reduction over the 11 events of 14 MW, while commercial customers provided an average of 5 MW. Residential impacts ranged from a low of 10 MW on September 29th, to a high of 26 MW on September 27th, 2010 (the day of SDG&E's all-time system peak). Residential load reduction as a percentage of reference load was fairly stable across events at around 55%. Commercial impacts were steadily around 4.7-5.3 MW, with the exception of September 27th, when commercial customers provided 7 MW of load reduction. Commercial load reduction as a percentage of reference load was also fairly stable at around 21%.

Residential customers accounted for 65% of enrolled tonnage and more than 70% of the total load reduction. The average load reduction for residential at 0.13 kW/ton exceeds that for commercial customers at 0.09 kW/ton. All else being equal, we would expect residential load reductions per ton to be lower than for commercial customers because commercial AC units run more regularly and are usually on at lower temperatures. However, in this case, commercial units are subject to less severe load control because the options are either 50% or 30%, as opposed to 100% or 50% for residential. Also, commercial customers face cooler weather on average. Therefore, residential customers provide higher load reduction as a percentage of the reference load than commercial customers. Residential customers are split evenly between 50% and 100% cycling. About 60% of commercial customers are on 30% cycling, with the rest on 50% cycling.

Table 1-1:
2010 Average Hourly Load Reduction for Event Period by Event Day
All Residential Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.19	0.10	53	11	85
7/16/2010	Friday	0.27	0.14	52	15	88
8/17/2010	Tuesday	0.20	0.11	56	12	85
8/18/2010	Wednesday	0.25	0.14	56	15	87
8/19/2010	Thursday	0.21	0.12	57	13	85
8/23/2010	Monday	0.22	0.12	56	13	87
8/24/2010	Tuesday	0.23	0.13	55	13	88
8/25/2010	Wednesday	0.21	0.11	52	11	85
9/27/2010	Monday	0.48	0.25	51	26	95
9/28/2010	Tuesday	0.22	0.13	57	13	84
9/29/2010	Wednesday	0.18	0.10	55	10	82
	AVERAGE	0.24	0.13	55	14	86

Table 1-2:
2010 Average Hourly Load Reduction for Event Period by Event Day
All Commercial Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.41	0.09	21	4.7	83
7/16/2010	Friday	0.48	0.10	20	5.2	85
8/17/2010	Tuesday	0.39	0.08	22	4.7	82
8/18/2010	Wednesday	0.46	0.09	20	5.2	84
8/19/2010	Thursday	0.43	0.09	21	4.9	82
8/23/2010	Monday	0.41	0.09	21	4.7	84
8/24/2010	Tuesday	0.43	0.09	21	4.9	85
8/25/2010	Wednesday	0.42	0.09	21	4.8	82
9/27/2010	Monday	0.63	0.12	20	6.8	92
9/28/2010	Tuesday	0.43	0.10	23	5.3	83
9/29/2010	Wednesday	0.39	0.09	23	4.9	81
	AVERAGE	0.44	0.09	21	5.0	84

Table 1-3:
2010 Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.26	0.10	42	16	84
7/16/2010	Friday	0.34	0.12	41	21	87
8/17/2010	Tuesday	0.26	0.10	44	16	84
8/18/2010	Wednesday	0.32	0.12	44	20	86
8/19/2010	Thursday	0.28	0.11	45	17	84
8/23/2010	Monday	0.29	0.11	44	18	86
8/24/2010	Tuesday	0.30	0.11	44	18	87
8/25/2010	Wednesday	0.28	0.10	41	16	84
9/27/2010	Monday	0.54	0.20	40	32	94
9/28/2010	Tuesday	0.29	0.12	45	18	84
9/29/2010	Wednesday	0.25	0.10	44	15	82
	AVERAGE	0.31	0.12	43	19	86

There is a clear selection bias among residential participants, with customers in cooler regions being more likely to choose 100% cycling. The average temperature during events for customers on 50% cycling was 88.4°F, while for customers on 100% cycling it was 85.9°F. This leads to larger reference loads among 50% cycling customers and to impacts that are very similar between the two cycling groups, even though the average size of AC units is similar across groups. The average hourly event impact for each group for 2010 is 0.56 kW.

In light of this, and the fact that the residential 100% cycling group is paid four times as much to participate as 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.

2 Introduction and Program Summary

SDG&E's Summer Saver program is a demand response resource based on AC 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 2010 and ex ante estimates for 2011 through 2021.

2.1 Program Overview

The Summer Saver program is available to residential customers and commercial facilities with peak demand up to 100 kW on average during a given 12-month period. For customers enrolled in the program, events may be called on weekdays and/or weekends (depending on the customer's preference) between May 1st and October 31st. Events must be between 2-hours and 4-hours in duration and cannot be called for more than 40 hours per month or 120 hours per year. Event days cannot include holidays or be called on more than three days in any calendar week.

Summer Saver is classified as a "day-of" demand response program and does not notify participating customers when an event is being called. 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, 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 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 nine 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 is summarized in Table 2-1. As of November 2010, there are 31,295 customers enrolled in the program, which in aggregate had about 161,000 tons of air conditioning capacity. About 80% of participants were residential customers who accounted for 65% of the total tons of cooling subject to control under the program. Just over 50% of residential participants were on the 100% cycling option and roughly 40% of commercial customers were on the 30% cycling option. Summer Saver enrollment is expected to remain roughly constant in the future.

Table 2-1:
Summer Saver Enrollment

Customer Type	Cycling Option	Enrolled Customers	Enrolled Tons
Commercial	30%	2,578	21,324
	50%	3,729	33,454
	Total	6,307	54,778
Residential	50%	12,340	49,170
	100%	13,278	57,246
	Total	25,618	106,416
Grand Total		31,925	161,194

2.2 Event and Load Research Sample Summary

In 2010, 11 Summer Saver events were called. Table 2-2 shows the dates and timing of each event. All residential and commercial accounts in the load research sample were called for each event. All events were four hours long and each one began either at 1 PM or 2 PM.

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 750 customers in the final estimating sample, 229 commercial and 143 residential AC units were in group A and 239 commercial and 139 residential AC units were in group B. As shown in Table 2-2, groups A and B alternated between the curtailed and comparison groups from one event to the next.

This experimental design is very useful in that it allows for an almost immediate measurement of the effect of a recent event through comparison of the two groups' loads. It also allows more certainty in measured load impacts because reference loads can be estimated in two independent ways: by measuring loads during event-like times for the curtailed group; and by measuring loads during events for the non-curtailed group. The experimental structure is used for this purpose in this report.

Table 2-2:
Summer Saver 2010 Event Summary

Date	Day of Week	Start Time	End Time	Group Called
7/15/2010	Thursday	1 PM	5 PM	A
7/16/2010	Friday	1 PM	5 PM	B
8/17/2010	Tuesday	1 PM	5 PM	A
8/18/2010	Wednesday	1 PM	5 PM	B
8/19/2010	Thursday	1 PM	5 PM	A
8/23/2010	Monday	1 PM	5 PM	B
8/24/2010	Tuesday	1 PM	5 PM	A
8/25/2010	Wednesday	1 PM	5 PM	B
9/27/2010	Monday	2 PM	6 PM	A
9/28/2010	Tuesday	2 PM	6 PM	B
9/29/2010	Wednesday	2 PM	6 PM	A

Load impact analysis was based on end-use level data from the sample of residential and commercial customers described below. Whole building data were also used to estimate load impacts for residential and commercial customers in order to compare the predicted values based on the two different measures of usage.

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 records whole-house energy usage and the other records the energy usage of a single air conditioner. These meters were deployed over the course of 2006-2008.

FSC installed AC loggers to record usage values at five-minute intervals on commercial Summer Saver AC units. Recruited customers received an incentive check for $30 upon installation of the AC logger. A total of 500 AC loggers were installed on commercial units, with some commercial premises having as many as 3 loggers installed on separate AC units. When loggers were installed at sites with more AC units than loggers, a randomization procedure was used to select the AC unit to receive the logger.

During installation, technicians came across 29 cases[1] where the AC was broken and 20 cases where the load control switch was missing, broken or disconnected. In these cases, a replacement recruit was used instead of installing a logger at a site where impacts would be zero.[2] Commercial load impacts were adjusted to reflect these 49 cases.

1 This is a high number of non-working AC units, significantly higher on a percentage basis than three other utility clients that FSC installed devices on. We are double checking our record keeping to make sure there is no mistake on our end. We will let you know if there is but if not, this may be something SDG&E (or Comverge) would want to look into.

2 In these cases, FSC provided SDG&E with a list of the involved central AC units so that SDG&E could remove them from the Summer Saver customer list.

Cases of broken ACs are accounted for by multiplying predicted loads with and without DR by:

$$\frac{500\ working ACs}{500 + 29\ ACs\ with\ working\ DLC} = 0.95$$

Broken switches were accounted for by multiplying load impacts by:

$$\frac{529\ ACs\ with\ working\ switches}{549\ ACs\ observed} = 0.96$$

The two cases are treated differently because ACs with broken switches contribute load, but no load impact, while broken ACs contribute neither.

Table 2-3 shows the distribution of AC tonnage by climate zone and program option for the commercial population and sample as of September 27th, 2010, the system peak day. The sample and the population match quite closely.

Weights were created within the commercial and residential sectors to make sure that the impact values represent the Summer Saver population. The weights were created by comparing the distribution of aggregate AC tonnage for the population and the load research sample.

The weights were calculated by dividing the population percentage by the sample percentage in each cell. For example, weekday-only customers on 30% cycling in climate zone 1 account for 14.9% of the total AC tonnage in the population and 13.3% in the sample. Therefore, these customers are underrepresented in the sample and should have a relatively higher weight. The weight was calculated by dividing 14.9% by 13.3%, which equals 1.12. For a segment that is overrepresented in the sample, the weight will be below one.

Table 2-3:
Distribution of AC Tonnage by Climate Zone and Program Option
Commercial Population

Cycling and Weekday Options	Group	Climate Zone 1	Climate Zone 2	Climate Zone 4	Total
30% Mon-Fri	Population	14.9	0.4	22.2	37.5
	Sample	13.3	0.2	23.8	37.3
30% Mon-Sun	Population	0.6	0	0.9	1.5
	Sample	1.1	0	1.0	2.1
50% Mon-Fri	Population	30.3	0.3	28.0	58.6
	Sample	29.6	0.3	28.1	58
50% Mon-Sun	Population	1.4	0	1.2	2.6
	Sample	1.5	0	1.3	2.8
Total	Population	47.2	0.7	52.3	100
	Sample	45.5	0.5	54.2	100

Table 2-4 shows the distribution of AC tonnage by climate zone and program option for the residential population and sample. The residential sample does not have any representation for approximately 0.6% of the residential tonnage in the Summer Saver residential population. Also, climate zone 1 is under-represented. Customers on the weekday-only option in climate zone 1 account for 9.1% of the population but only 0.5% of the residential sample. For this reason, climate zone 1 was merged into one group for the sake of weighting. Otherwise, the weekday-only customers in climate zone 1 would be heavily weighted. This would introduce substantial unwanted variance into the result because there are only a few weekday-only customers.

Table 2-4:
Distribution of AC Tonnage by Climate Zone and Program Option
Residential Population

Cycling and Weekday Options	Group	Climate Zone 1	Climate Zone 2	Climate Zone 3	Climate Zone 4	Total
100% Mon-Fri	Population	6.5	0.2	0	22.7	29.4
	Sample	0.3	0	0	16.4	16.7
100% Mon-Sun	Population	4	0.4	0	18.4	22.8
	Sample	2.5	1	0	44.1	47.6
50% Mon-Fri	Population	2.6	1	0	40.7	44.3
	Sample	0.2	0.7	0	31	31.9
50% Mon-Sun	Population	0.4	0	0	3.1	3.5
	Sample	0	0	0	3.7	3.7
Total	Population	13.5	1.6	0	84.9	100
	Sample	3	1.7	0	95.2	100

2.3 Report Structure

The remainder of this report is organized as follows. Section 3 summarizes the methodologies that were used to develop the ex post load impacts and the validation tests that were applied to assess the accuracy of the estimates. It also discusses some of the issues that should be considered when interpreting results for subsamples of customers or when assessing the distribution of impacts across populations. Section 4 contains the ex post load impact estimates and Section 5 presents the ex ante estimates and recommendations.

3 Analysis Methodology

This section summarizes the analysis methods that were used to estimate ex post load impacts for each event and for the average event. Results from a variety of validation tests are also presented.

Load impact estimates are based on regression analysis of end-use data. For residential customers, two additional methods were used to corroborate the primary results. First, load impacts were calculated by direct comparison of AC loads between groups A and B. Second, impacts were calculated using regression analysis of whole-building data. For commercial customers, the first corroborating analysis was performed, but not the second due to complications in identifying the whole-building meter associated with each participating commercial AC unit.

The primary residential analysis is based on data from 268 premises with data covering the entire summer of 2010. The commercial analysis is based on data from 482 commercial premises covering the same period. A total of 500 commercial loggers were installed. Three were lost and eight were broken during the summer. Seven showed all missing values for the dates of the study.

Separate linear regressions were done for each AC unit in each sample, but using a common model specification. The regression specification was:

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

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

Table 3-1:
Description of AC Load Regression Variables

Variable	Description
a	Estimated constant
$b - e$	Estimated parameter coefficients
I_h	Indicator variables representing the hours of the day, designed to estimate the effect of daily schedule on usage behavior and event impacts
I_w	Indicator variable for weekend days
I_e	Indicator variable to pick up the effects of events
I_{pe}	Indicator variable to pick up the effects of post-event periods. Decreases in magnitude over the four hours after the event at a rate of 67% per hour to reflect that snap-back should die off fairly quickly
$wacdh_t$	Weighted average of the previous 12 hours of cooling-degree hours with a base of 70°F, weights

Variable	Description
	decrease 10% per hour so that recent hours have a stronger effect

The conceptual basis for statistical analysis is that with large sample sizes, the effect of unobservable or omitted factors not related to the main effect will disappear due to the power of averaging. Presumably, many factors affect individual-customer AC usage other than what can be included in a large-scale model. In a large sample, such as hundreds of customers over three months, it is likely that the effect of these omitted factors is small. However, in smaller samples, such as one or a few customers' regression models, these omitted factors could have an important effect. This means that results for sub-samples of the dataset should be viewed with increasing caution as the samples decrease in size.

In models of AC load, these omitted factors take two main forms:

- Individual-specific factors such as work schedules, vacation timing and individual temperature preferences; and
- Observable factors for which there is not enough data to properly model their effect. A frequent example of this is relatively rare weather patterns that might occur only once in a summer, such as a thunderstorm in the middle of an event or a very hot day with a very cold morning.

The challenges faced in modeling air conditioning usage as a function of weather can be seen by examining Figures 3-1 and 3-2. Figure 3-1 shows hourly average AC load for the residential sample on two non-event weekdays with similar temperature profiles. The days are July 13th, and September 3rd. The average temperature is the same on both days at 70°F. Their daily high temperatures are close, at 82 and 85°F, respectively. Figure 3-2 shows their hourly temperatures for reference.

The point of the figures is to illustrate that there can be large differences in AC usage that may be unexplainable using simple functions of recent temperature. For example, September 3rd has peak AC load three times higher than July 13th, despite similar temperature profiles. One possible explanation is that September 3rd was the Friday before Labor Day and many people may have taken the day off, which could lead to higher residential air conditioning use than on a typical weekday. Regardless of the actual cause, this illustrates the difficulty of building a valid predictive model that will forecast on both of these days with high accuracy using few enough variables for the sample to support. This "unexplainable" difference between these days provides calibration for the amount of accuracy and precision to expect from a model of AC usage when the only observable variable is the weather.

An explanation for the differences between the days might be found by examining whether the difference is due to temperatures from the day before. In that way, an omitted factor could become an included factor in the model. However, every such variable added to the model increases the necessary data for the model to do a good job matching real patterns. In the case where load depends on the previous day, a good model requires information about both the current temperatures and temperatures perhaps as much as 36 hours in the past. If each AC usage prediction requires 36 previous hours of temperature data to model, then the effective sample size of the dataset is much smaller than if AC usage can be modeled well using the last 12 hours of temperature, for example. This is because there are 3 times as many non-overlapping 12-hour temperature blocks as there are 36-hour temperature blocks in the data.

In this report we attempt to strike a balance between using all the data by accounting for different effects of weather, and not over-straining the data by trying to make it fit patterns that are not well-represented. This necessarily means there will be unexplained variation, similar to the variation shown in Figure 3-1. This should be kept in mind when interpreting estimated load impacts. The same point applies to the commercial AC load model.

Figure 3-1:
Average Hourly AC Load on Two Days with Similar Temperatures

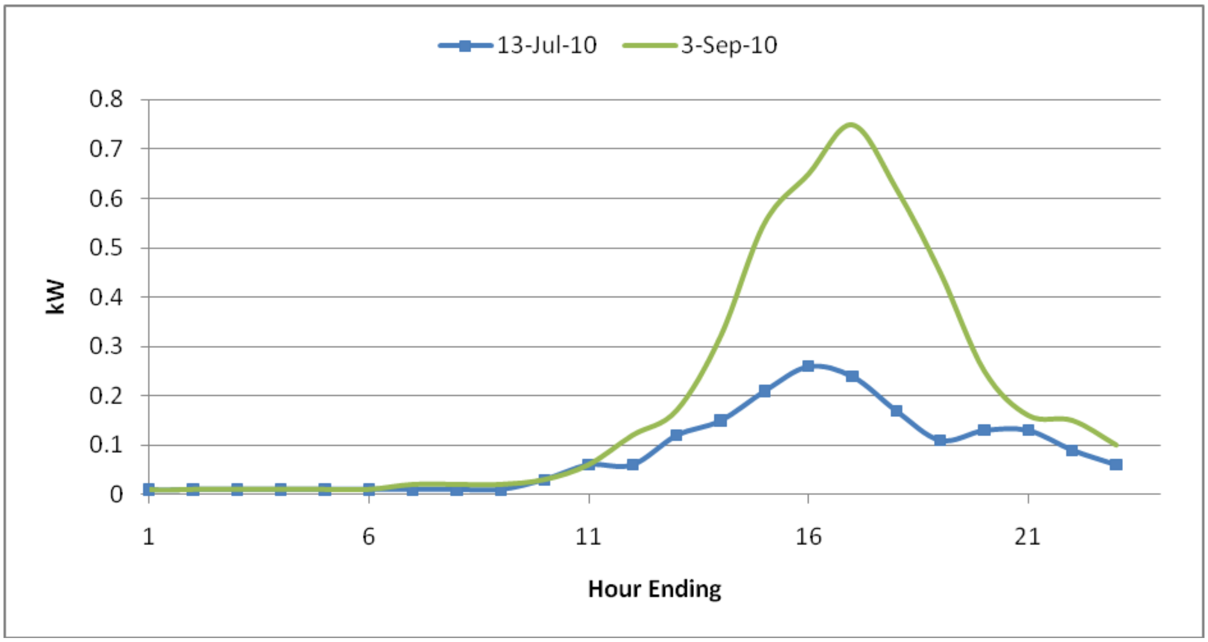
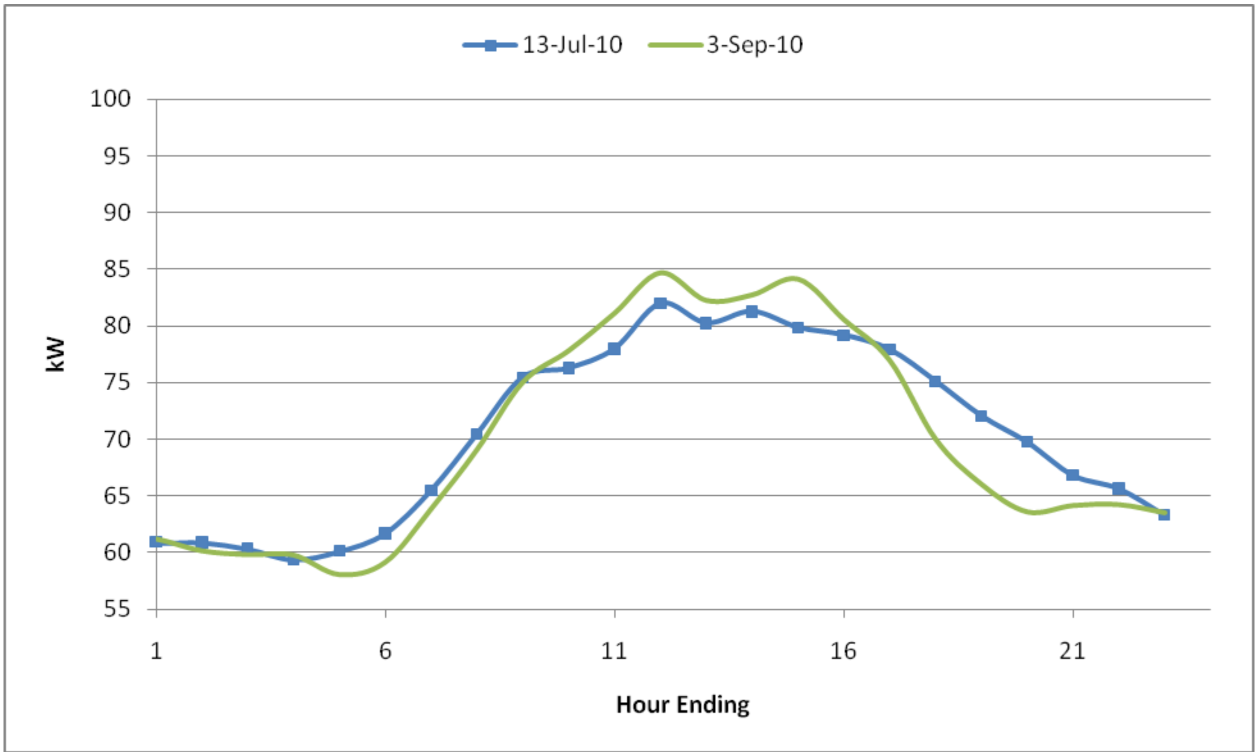


Figure 3-2:
Average Hourly Temperatures on the Two Days in Figure 3-1



A related issue is that any measure of event-impact standard error associated with these individual-AC unit regressions inherently assumes that the model has been fully and correctly specified so that the only remaining unexplained variation is completely random—meaning that it is unrelated to any variables of interest. As noted, this is almost certainly untrue at an individual-AC unit level. Moreover, statistical variation can only be calculated based on the observed events during the study period. This means that it cannot take into account the effect of weather patterns or other recurring behavior patterns that are not well-represented in the dataset, but that are likely to arise in the future. When the statistical model is asked to provide an extrapolation, there is no procedure for telling it to adjust its uncertainty estimate upward because it's an extrapolation. Both of these issues probably lead to an under-estimation of the true level of variance that should be expected in Summer Saver results—even assuming no operational changes or changes in underlying customer behavior. The degree of this under-estimation is unknown because there is no data to model it.

Given that caveat, standard errors for load impacts are calculated as

$$se = \sqrt{(stdp^2 + rmse^2)},$$

where *stdp* is the standard deviation of the prediction—i.e., the standard error associated with the fact that all coefficients are estimated values—and *rmse* is the root-mean-squared-error of the regression, or the error associated with the fact that the model has a baseline of uncertainty in it even if coefficients are estimated perfectly. The *stdp* value is calculated individually for each hourly prediction of each customer's load.

Having calculated the standard error for each customer for each hour, aggregate standard errors are calculated assuming that errors are independent across customers. Therefore, variances can be summed to get aggregate variance.

Having calculated standard errors of predicted load, percentiles of load impacts are calculated based on a Gaussian (or Normal) distribution with standard deviation equal to the calculated standard error and mean equal to the estimated load impact. This calculation is justified by the central limit theorem.

3.1 Model Validation

In order for a model to be useful in the context of Summer Saver, it must make accurate predictions of AC loads, primarily at high temperatures. Three methods of validation are used to assess this capability.

3.1.1 In-sample Testing

First, at an individual level and an aggregate level, the model must explain a large degree of the observed variation in AC load during the summer of 2010. This is a test of the in-sample R-squared of the model. This is the simplest test for the model to pass and it is a necessary, but not sufficient condition for the model to be useful. A model with a high R-squared value can be developed by including a very large number of variables. In this case, the model will appear to explain a large degree of the variation in load, but it may be highly inaccurate in predicting for conditions outside of the range of values for the data used to estimate the model. This is known as over-fitting.

Although the regressions were performed at the individual AC unit level, from a policy standpoint, the focus is less on how the regressions perform for individual AC units than on how they perform for the average participant and for specific customer segments. We present measures of the variation accounted for by the model, as described by the R-squared goodness-of-fit statistic, for the individual regressions and for aggregate load.

The average R-squared among residential AC unit regressions is 43% and among commercial AC unit regressions is 45%. At an aggregate level over the hours of the summer, the commercial model accounts for 94% of the variation in AC usage and the residential model accounts for 80%.

Summer Saver events are only likely to be called at times of very high temperature, therefore the models must accurately fit load at high temperatures in particular. Figures 3-3 and 3-4 show that they do so for the high-temperature periods during the summer of 2010. Figure 3-3 shows the average actual hourly load in the residential sample and the predicted hourly load for afternoon non-event hours between 1 PM and 6 PM when the temperature exceeds 80°F. Figure 3-4 shows the same for commercial customers. Bias in these figures would show itself as a persistent difference between actual and predicted values in one direction. For example, if the actual values strongly tended to be above the predicted values, then that would indicate that the model under-predicted load at high temperatures. All else being equal, that would indicate the model is likely to understate event impacts.

There is little systematic difference between the predicted and actual loads in either figure. On average, residential predicted loads exceed the actual loads by 9%. For commercial loads, actual loads exceed predicted loads by an average of 10%.

Because these predicted values are predictions for conditions used to fit the model, these figures do not necessarily indicate that the model is good at predicting in an ex ante sense. Instead, these figures show that there is only a small amount of variation in the existing data that the model does not account for.

Figure 3-3:
Actual and Predicted Average Residential Load for 1 PM to 6 PM, Non-event Days When the Temperature Exceeds 80°F

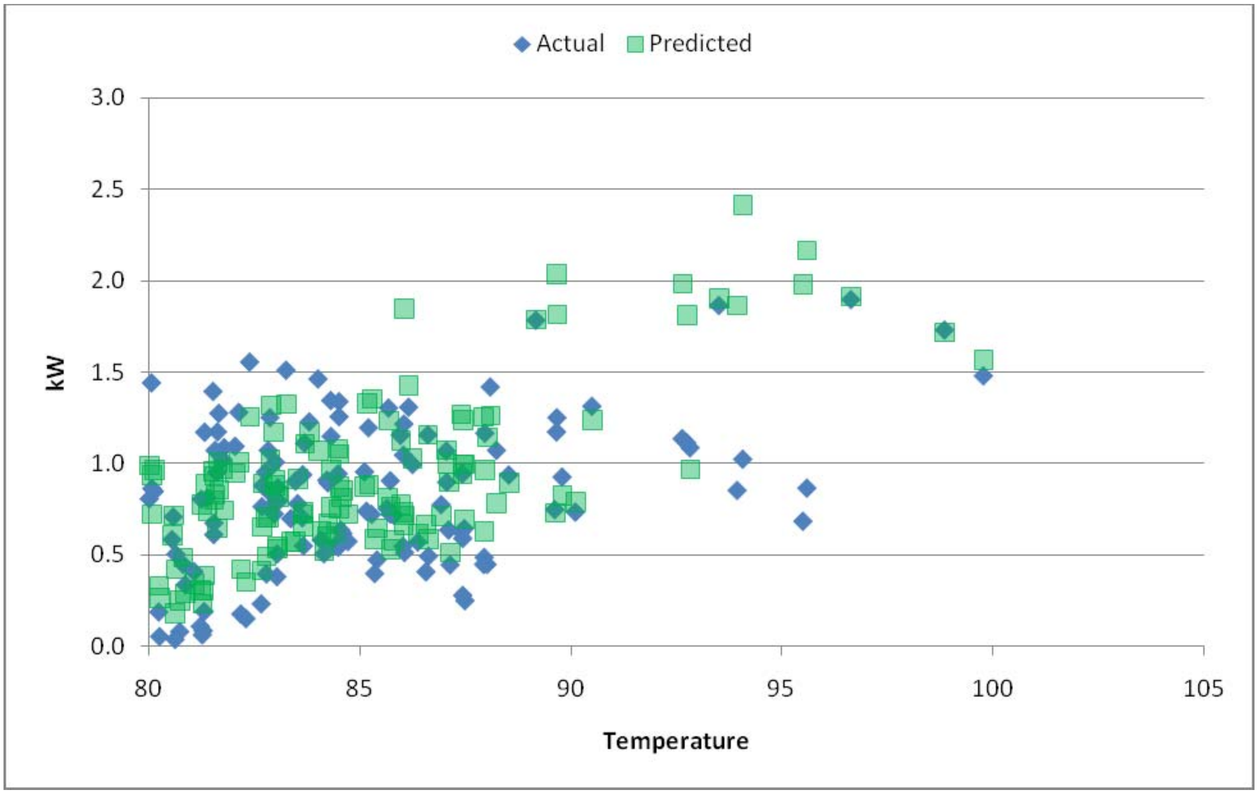
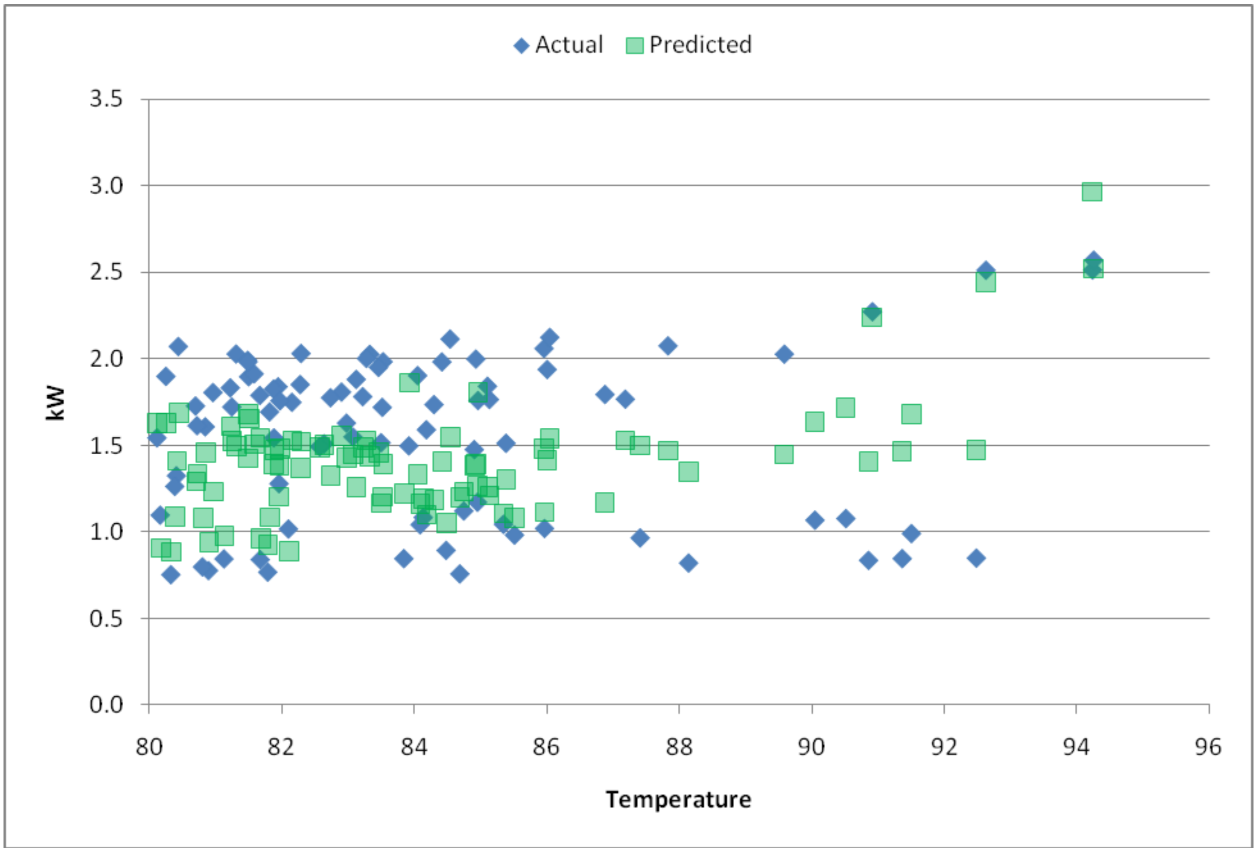


**Figure 3-4:
Actual and Predicted Average Commercial Load for 1 PM to 6 PM, Non-event Days When the Temperature Exceeds 80°F**



In addition to checking how well the model predicts load at non-event times, it is also important to verify that the model predicts load well during event periods. Figures 3-5 and 3-6 are the event period counterparts to Figures 3-3 and 3-4. They show the average actual and predicted hourly load in the M&E samples for event hours when the temperature exceeds 80°F for residential AC units and commercial units, respectively. For residential AC units, the predicted load exceeds the actual load by an average of 8%. For commercial AC units, the average difference is 1% of actual load, or about 0.09 kW, with actual values being higher on average.

Figure 3-5:
Actual and Predicted Average Residential Load for Event Hours When the Temperature Exceeds 80°F

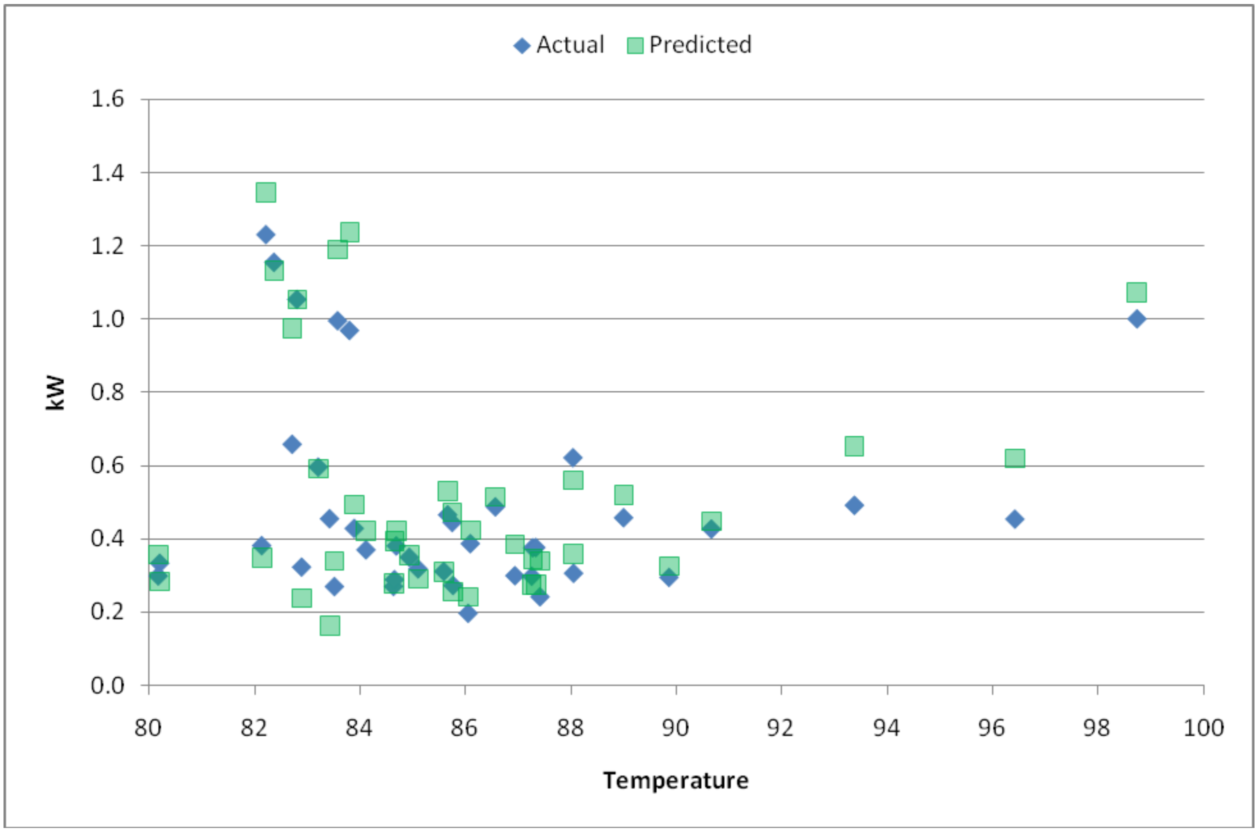
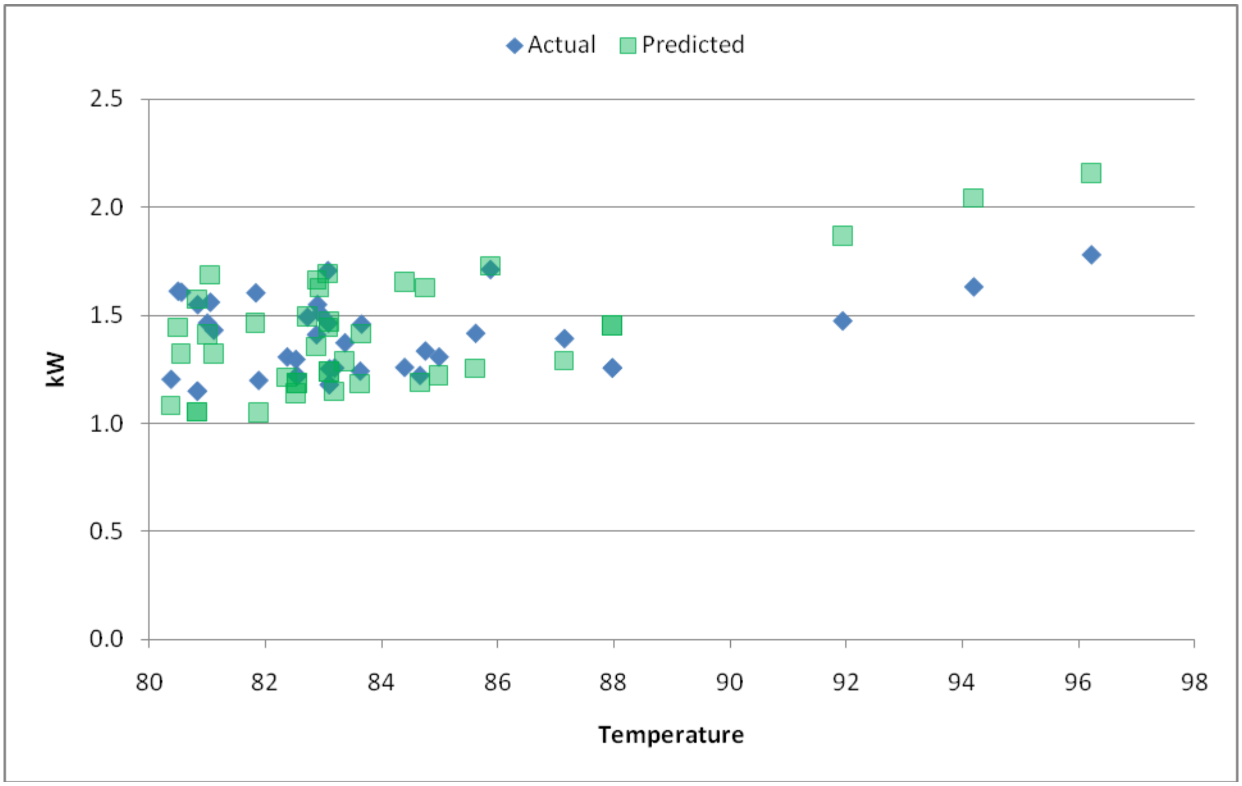


Figure 3-6:
Actual and Predicted Average Commercial Load for Event Hours When the Temperature Exceeds 80°F



3.1.2 Out-of-Sample Testing

As a second and more stringent test, the model must do well in out-of-sample testing on days included in the 2010 dataset. The procedure for out-of-sample testing consisted of running the regression models multiple times, each time holding back some of the hot non-event days of the summer from the estimation. Then predicted loads were compared to actual loads on the days held back. This is a true test of the regression model's predictive power for weather conditions actually observed during the summer of 2010. For the Summer Saver sample, the appropriate out-of-sample days are easy to pick, as it makes sense for group A and B to use the days when that group was the control group. That makes this a direct test of the model's ability to predict loads on days when events took place.

Figure 3-7 shows the actual average hourly energy use of residential AC units on event days when each customer was used as a control group customer compared to the regression-predicted average energy use. Figure 3-8 shows the same for commercial AC units. The close match between predicted values and actual values reflects the ability of the regressions to predict accurately. In both cases, the predicted load is very close to the actual load. For residential customers, the predicted load is, on average, less than 1% lower than actual load during the hours of 1 PM to 6 PM. For commercial customers, predicted load is virtually identical to actual load. That the commercial result is so accurate is something of a coincidence. The residential result more accurately depicts the level of accuracy to be expected.

Figure 3-7:
Average Residential AC Unit Actual and Predicted Load for Out-of-Sample Days

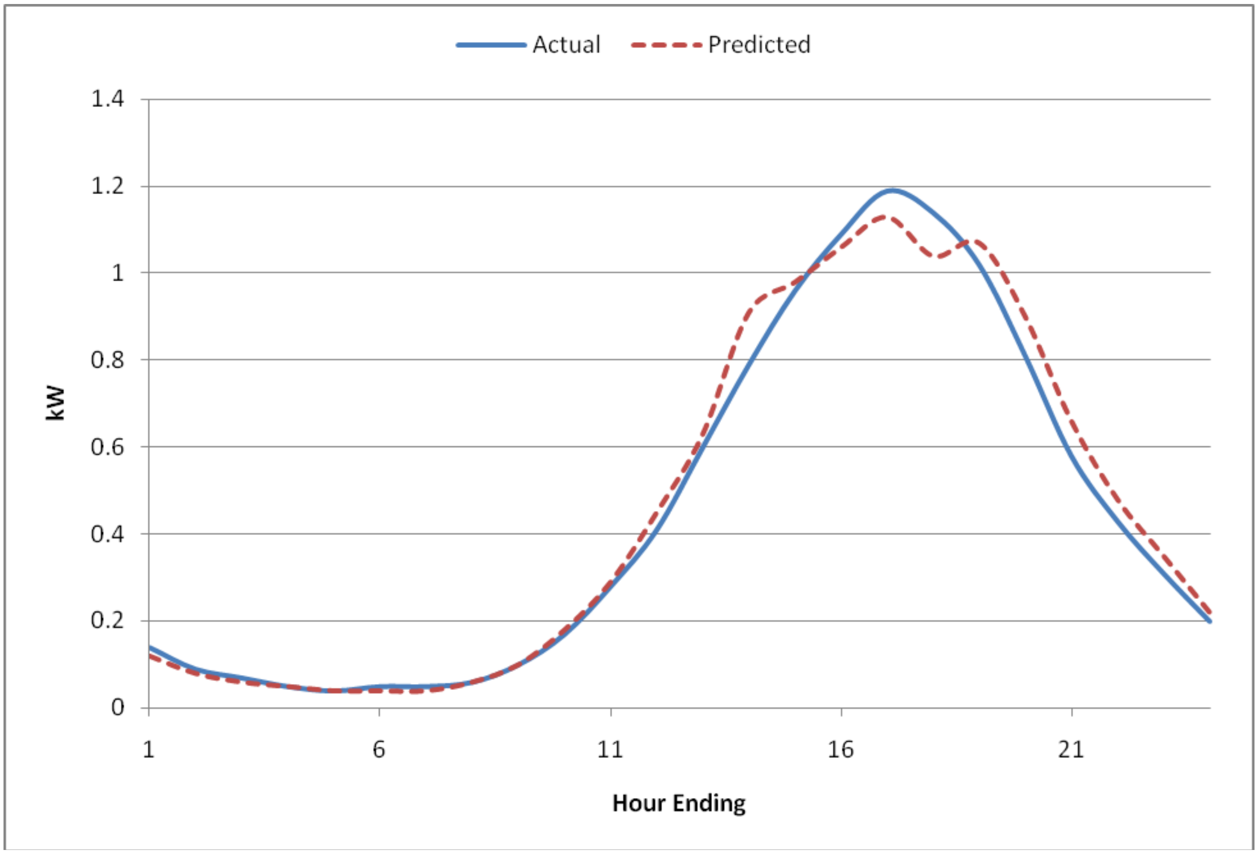
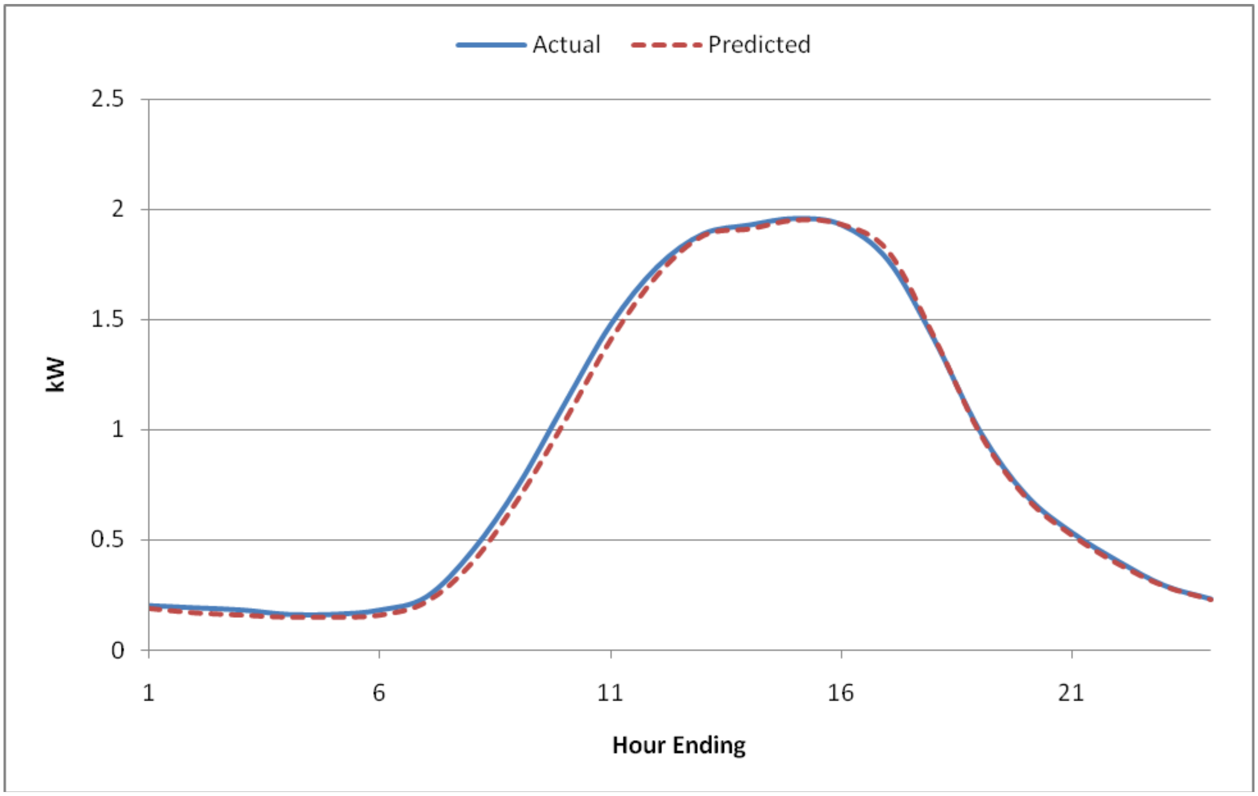


Figure 3-8:
Average Commercial AC Unit Actual and Predicted Load for Out-of-Sample Days



The final test that the model must pass is one of general plausibility in predicting for the ex ante weather conditions. This test is less well-specified, but consists of producing reasonable AC load patterns as a function of weather, as compared to results in past years, results from other programs and general knowledge about how the program works. This reality-check test is a crucial way to test the assumptions that go into the model. The ex ante estimates that are presented in Section 5 were carefully reviewed and generally display the expected patterns across event conditions and are consistent with other studies after judgmentally accounting for expected differences due to weather conditions and other factors.

4 Ex Post Load Impact Estimates

4.1 Comparison of Impacts Under Alternative Estimation Methods

As a further check on the results of the regression models, and for the purpose of showing that other methods of measurement can be viable, Table 4-1 shows the impacts from the individual AC-unit regressions compared to impacts measured using two other methods. One method is used for both residential and commercial customers. It consists of calculating the load impact as the difference between the weighted average load of group A and group B for each event hour. This method provides a useful check on the results based on the regression analysis. The primary assumption behind the individual AC unit regressions is that customer loads at other times of the summer with similar weather conditions provide a good prediction for the load if there was no event. The primary assumption behind the alternative analysis is that the load of similar customers who did not experience events is a good estimate of what load would have been in the event group if there had been no event.

Impacts are shown on a per premise basis for residential customers and a per AC-unit basis for commercial customers.

The second alternative approach is applied only to residential customers and consists of individual-customer regressions on whole-building data. This is not used for commercial customers due to difficulties in matching the controlled AC with the correct meter for many commercial customers.

For residential customers, all three methods produce very similar results. The average impact over all events is quite similar for all three methods and even the individual event-day impacts are generally similar. Indeed, given the magnitude of the standard errors for each impact estimate, for residential customers only one of the differences in the table is statistically significant at the 95% confidence level, which is to be expected in a table with more than 20 comparisons being made at 95% confidence each. The one statistically significant difference is between the AC-regression result and the comparison model on September 27th. There are a couple of instances where the two regression methods are similar and the subtraction method differs by a fair amount. The comparison method contains a fairly large amount of sampling variance. The two groups are well-matched, but random differences in average load between them occur fairly often during non-event times.

That the whole-building regression produces similar results as the end-use regression was also found in the 2009 Summer Saver evaluation. This will be useful in future evaluations. Currently, smart meters with ability to provide hourly interval data are deployed at roughly 50% of Summer Saver premises. This means that in the near future it may be possible to produce highly accurate impact estimates for residential customers without the use of a load-research sample. The same might also be true for commercial customers if the correspondence between controlled AC units and whole-building meters could be determined accurately. However, the impacts for commercial customers may be harder to detect from whole building data because of the lower cycling strategies employed in the commercial segment and the lower “signal to noise” ratio that exists when trying to detect these smaller impacts from usage with high variability.

For commercial customers, the average of each method over all the events is very close between the two methods. The commercial sample had a noticeable average difference between groups A and B. Group A tended to have lower loads at high temperatures than group B. This leads the subtraction method to overestimate the impact of events on Group A event days and underestimate the impact on Group B event days. This can be seen by looking at the last column in Table 4-1, where the difference between event impacts calculated using the two methods alternates from negative to positive based on which group got each event. Over all the events, this bias almost averages out completely so that the average effect for the two methods is similar.

Table 4-1:
Comparison of Event Impacts Calculated Using Three Methods (kW)

	Residential			Commercial		
	Individual Regression	Group Comparison	Whole-Building Regression	Individual Regression (1)	Group Comparison (2)	(1)-(2)
July 15	0.43	0.40	0.47	0.38	0.68	-0.30
July 16	0.59	0.58	0.43	0.42	0.25	0.17
August 17	0.46	0.38	0.50	0.38	0.59	-0.21
August 18	0.58	0.58	0.62	0.42	0.33	0.09
August 19	0.50	0.53	0.54	0.39	0.67	-0.28
August 23	0.52	0.34	0.56	0.38	0.25	0.13
August 24	0.53	0.61	0.56	0.40	0.71	-0.31
August 25	0.46	0.66	0.49	0.39	0.18	0.21
September 27	1.03	1.36	1.14	0.55	0.74	-0.19
September 28	0.53	0.55	0.60	0.43	0.20	0.23
September 29	0.42	0.36	0.49	0.40	0.43	-0.03
Average	0.55	0.58	0.58	0.41	0.46	-0.04

4.2 Final Ex Post Estimates

This report section contains the ex post load impact estimates for program year 2010. Tables 4-2 through 4-4 show the load impacts for residential, commercial and all customers combined in 2010. Summer Saver residential customers delivered an average aggregate load reduction over the 11 events of 14 MW, while commercial customers provided an average of 5 MW. Residential impacts ranged from a low of 10 MW on September 29th, to a high of 26 MW on September 27th, 2010 (the day of SDG&E's all-time system peak). Residential load reduction as a percentage of reference load was fairly stable across events at around 55%. Commercial impacts were steadily around 4.7-5.3 MW, except on September 27th, when commercial customers provided 7 MW of load reduction. Commercial load reduction as a percentage of reference load was also fairly stable at around 21%.

Residential customers accounted for 65% of enrolled tonnage and 70% of the total load reduction. The average load reduction for residential at 0.13 kW/ton exceeds that for commercial customers at 0.09

kW/ton. All else being equal, we would expect residential load reductions per ton to be lower than for commercial customers because commercial AC units run more regularly and are usually on at lower temperatures. However, in this case, commercial units are subject to less severe load control because the options are either 50% or 30%, as opposed to 100% or 50% for residential. Also, commercial customers face cooler weather on average. Therefore, residential customers provide higher load reduction as a percentage of the reference load than commercial customers. Residential customers are split evenly between 50% and 100% cycling. About 60% of commercial customers are on 30% cycling, with the rest on 50% cycling.

Table 4-2:
2010 Average Hourly Load Reduction for Event Period by Event Day
All Residential Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.19	0.10	53	11	85
7/16/2010	Friday	0.27	0.14	52	15	88
8/17/2010	Tuesday	0.20	0.11	56	12	85
8/18/2010	Wednesday	0.25	0.14	56	15	87
8/19/2010	Thursday	0.21	0.12	57	13	85
8/23/2010	Monday	0.22	0.12	56	13	87
8/24/2010	Tuesday	0.23	0.13	55	13	88
8/25/2010	Wednesday	0.21	0.11	52	11	85
9/27/2010	Monday	0.48	0.25	51	26	95
9/28/2010	Tuesday	0.22	0.13	57	13	84
9/29/2010	Wednesday	0.18	0.10	55	10	82
	AVERAGE	0.24	0.13	55	14	86

Table 4-3:
Average Hourly Load Reduction for Event Period by Event Day
All Commercial Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.41	0.09	21	4.7	83
7/16/2010	Friday	0.48	0.10	20	5.2	85
8/17/2010	Tuesday	0.39	0.08	22	4.7	82
8/18/2010	Wednesday	0.46	0.09	20	5.2	84

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
8/19/2010	Thursday	0.43	0.09	21	4.9	82
8/23/2010	Monday	0.41	0.09	21	4.7	84
8/24/2010	Tuesday	0.43	0.09	21	4.9	85
8/25/2010	Wednesday	0.42	0.09	21	4.8	82
9/27/2010	Monday	0.63	0.12	20	6.8	92
9/28/2010	Tuesday	0.43	0.10	23	5.3	83
9/29/2010	Wednesday	0.39	0.09	23	4.9	81
	AVERAGE	0.44	0.09	21	5.0	84

Table 4-4:
Average Hourly Load Reduction for Event Period by Event Day
All Summer Saver Customers

Date	Day of Week	Avg. Reference Load (kW/ton)	Avg. Load Reduction (kW/ton)	Percent Load Reduction (%)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
7/15/2010	Thursday	0.26	0.10	42	16	84
7/16/2010	Friday	0.34	0.12	41	21	87
8/17/2010	Tuesday	0.26	0.10	44	16	84
8/18/2010	Wednesday	0.32	0.12	44	20	86
8/19/2010	Thursday	0.28	0.11	45	17	84
8/23/2010	Monday	0.29	0.11	44	18	86
8/24/2010	Tuesday	0.30	0.11	44	18	87
8/25/2010	Wednesday	0.28	0.10	41	16	84
9/27/2010	Monday	0.54	0.20	40	32	94
9/28/2010	Tuesday	0.29	0.12	45	18	84
9/29/2010	Wednesday	0.25	0.10	44	15	82
	AVERAGE	0.31	0.12	43	19	86

4.3 Impacts by Cycling Option

Customers choose their cycling option, which means that for residential customers it is not safe to assume that 100% cycling customers necessarily provide larger impacts than 50% cycling customers. The same point holds for commercial customers with regards to the 50% and 30% options.

Table 4-5 shows the average reference load and load impact by cycling option for residential Summer Saver customers. Residential customers who chose the 50% cycling option had significantly higher average reference loads 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 are less likely to select a program option that shuts their air conditioner down completely on high-use days. This causes the 50% cycling customers to provide slightly greater load reductions than 100% cycling customers, even though their impacts as a percentage of the reference load are lower.

Such a selection effect is very small among commercial customers, with those on 50% cycling having only slightly smaller reference loads than those on 30% cycling.

Table 4-5:
Load Reductions by Cycling Option

	Cycling Strategy	Avg. Enrolled Tons	Avg. Reference Load (kW/Ton)	Avg. Load Reduction (kW/Ton)	Percent Load Reduction (%)	Aggregate Hourly Load Reduction (MW)	Avg. Temp. (°F)
Commercial	30%	21,324	0.46	0.07	16	1.5	84
	50%	33,454	0.43	0.11	26	3.7	84
	All	54,778	0.44	0.09	21	5.1	84
Residential	50%	49,170	0.32	0.14	43	6.8	88
	100%	57,246	0.20	0.12	64	7.1	85
	All	106,416	0.24	0.13	54	13.9	86

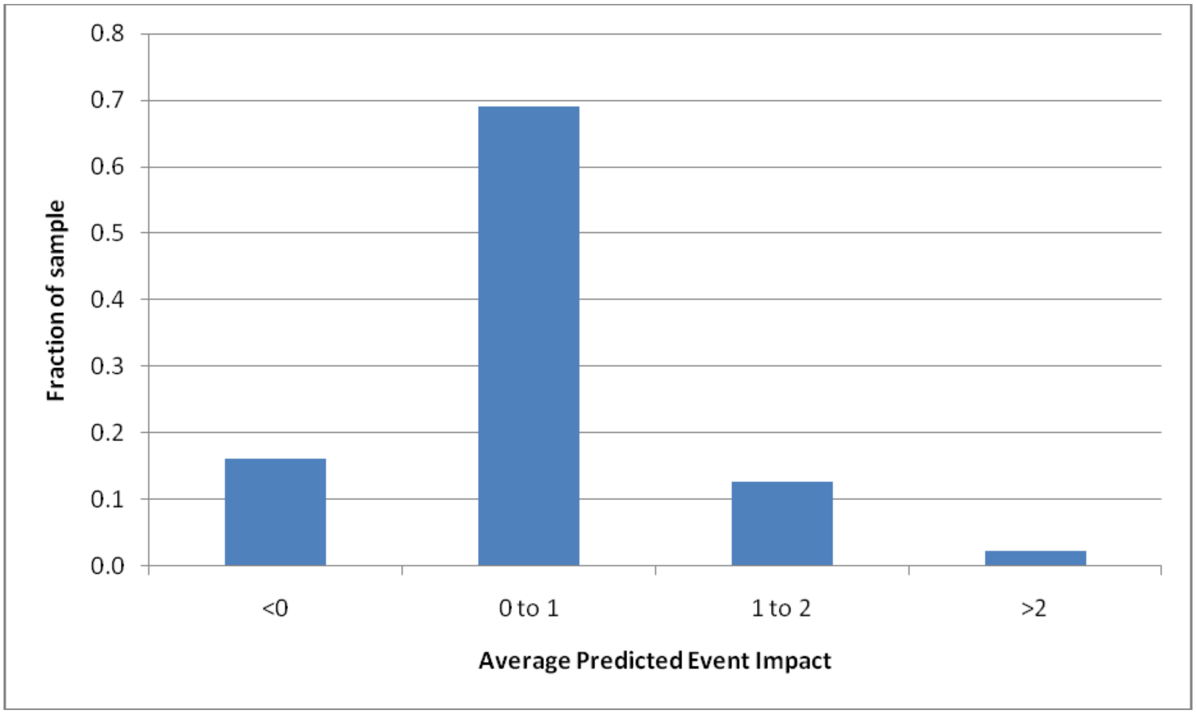
The above findings highlight an opportunity to improve program cost effectiveness by modifying the incentive differentials across cycling options among residential customers. The fact that the residential 100% cycling group is paid four times as much to participate as the 50% cycling group but actually produces lower average impacts indicates that cost effectiveness could be improved by increasing the share of program participants on the lower cost 50% cycling option and/or by reducing the incentive paid for 100% cycling while increasing the incentive paid for 50% cycling.

4.4 Distribution of Load Impacts and Free Riders

Figure 4-1 shows the distribution of predicted residential event impacts for a July 1-in-2 day at 3 PM. As was discussed in the methods section, results from any given AC unit regression should be assumed to include an unknown, but potentially substantial amount of bias due to omitted factors and small samples. Another way to put this, as it relates to Figure 4-1, is that over a longer period many customers who had small event impacts during 2010 might turn out to have high impacts and vice versa. This means that the values underlying Figure 4-1 are not completely reliable as predictors of future impacts on a customer-by-customer basis.

Based on visual inspection of load data, it appears that some of the cases of predicted negative impacts are due to communication failure—an issue addressed in the next section. However, this does not appear to account for all such cases. The remainder is due to small-sample and omitted factor biases.

Figure 4-1:
Histogram of Predicted Event Impacts for Individual Customers



A large number of customers have event-impact estimates within a small margin of zero. It is very unlikely that omitted variable bias would balance out true event effects to equal zero for such a large number of customers. This suggests that many customers are free-riders—taking part in the program because their AC would not be on during events anyway.

To address this issue, Table 4-6 shows the percentage of air conditioners in the sample that have average load less than 0.1 kW during each event period when that unit was part of the non-curtailed group. This should be a reliable indicator of those units' level of usage during event-like conditions, without load control. Units that have very little usage under such conditions are free-riders. Table 4-6 shows that for any given event, the proportion of free-riders is about 50% in the residential sample and close to 30% in the commercial sample. The table does not address whether these are the same customers for each event. The proportion of units with less than 0.1 kW of average load for 80% or more of event periods during the summer is 34% and 37% for residential units on 50% and 100% cycling, respectively and 20% and 22% for commercial units on 30% and 50% cycling respectively. These values are calculated over a total of only five or six events per customer, which means that they are subject to substantial sampling variance and might not predict well a customer's future load impact potential.

Table 4-6:
Fraction of Customers with Less than 0.1 kW Average Load During Control Periods

Event Date	Residential		Commercial	
	50% Cycling	100% Cycling	30% Cycling	50% Cycling
July 15	0.54	0.70	0.30	0.24
July 16	0.37	0.55	0.19	0.32
August 17	0.56	0.73	0.30	0.28
August 18	0.45	0.55	0.20	0.35
August 19	0.50	0.47	0.30	0.24
August 23	0.48	0.59	0.21	0.37
August 24	0.46	0.44	0.27	0.19
August 25	0.30	0.47	0.23	0.32
September 27	0.34	0.33	0.24	0.26
September 28	0.53	0.51	0.27	0.36
September 29	0.54	0.50	0.36	0.34
Average	0.46	0.53	0.26	0.30

4.5 Control Device Communications Failure

The load-control switches that cause events to happen at the customer level rely on radio signals for event activation. If the switch is broken, if the signal is blocked or if the signal is sent on a frequency that the device is not set up to receive, then the event will not occur for that device. This is referred to here as control device communication failure.

Direct measurement of control device communication was not done for the 2010 evaluation. However, customers on 100% cycling that do have event load drops of very close to 100% can be presumed to be affected by communication failure. Moreover, there is no obvious reason why customers on 100% cycling should have different communication failure rates from customers on other cycling options, so this analysis probably reflects communication across the Summer Saver population.

An analysis of the number of customers in the 100% cycling group that had load above 0.02 kW during each event hour of 2010 revealed that during the final three hours of an event, communication failure appeared fairly stable at around 13% of customers. The first hour was excluded because the events phase in over time, which means that 100% cycling customers often do not show the full impact in the first hour of the event. Failure did not affect the same customers for each event. About 40% of customers showed communication failure for more than 10% of event hours, 12% had failure for more than 50% of event hours and 5% showed failure for all event hours.

Communication failure and the fact that events phase in over time appear to account for the full difference between the 64% actual event impact for 100% cycling customers and the 100% expected impact. The customers with communication failure appear to have systematically higher load than those with successful communication. It is not clear whether this is a persistent and explainable pattern or a coincidence in the summer of 2010.

5 Ex Ante Impacts

The models developed from the ex post load data in 2010 were used to estimate load impacts based on ex ante event conditions and enrollment projections for the years 2011 through 2021. Enrollment is not expected to change in the future, so the tables represent predictions for the whole period 2011 through 2021. 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.[3] The ex ante event window is from 1 to 6 PM.

Tables 5-1 through 5-3 summarize the average and aggregate load impact estimates for residential, commercial and all Summer Saver participants. Aggregate impacts are based on steady enrollment levels equal to those as of fall 2010. Load impact estimates are presented for the average AC unit, for each ton of air conditioning and for participants as a whole. For a typical event with 1-in-2 year weather conditions, the average impact per AC unit is 0.38 kW for residential customers, and the reduction average per ton is 0.09 kW. Based on 1-in-10 year weather conditions, these values are almost 20% higher (0.45 kW and 0.11 kW/ton, respectively). The aggregate program load reduction potential for residential customers is 10 MW for a typical event day under 1-in-2 year weather conditions and 12 MW under 1-in-10 year weather conditions. These values are based on program enrollment of 106,416 tons of air conditioning.

Commercial customer predicted impacts are 0.31 kW per AC unit and 0.08 kW/ton for a typical event day in 1-in-2 year weather conditions. The aggregate impact during these weather conditions is 5 MW. Commercial impacts increase only slightly under 1-in-10 year weather conditions both due to the lower cycling options for commercial customers and due to commercial customers being located in cool weather areas.

There is significant variation in load impacts across months and weather conditions. Based on 1-in-2 year weather, the low temperatures in June, reflecting the well known “June Gloom” typically experienced in San Diego, result in small average and aggregate load impact estimates. The June 1-in-2 impact for residential customers is almost 70% lower than the October estimate, which is the highest of any month in 1-in-2 year weather conditions. For residential customers the June 1-in-10 year estimate is three times higher than the 1-in-2 year estimate. The weather conditions on the monthly system peak day in June and July produce the lowest value based on 1-in-10 year weather. The highest load impacts are in September in the 1-in-10 weather year, with the system peak estimate equaling 19 MW for the whole program.

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

Table 5-1:
Average and Aggregate Load Reductions by Day Type and Weather Year
All Residential Customers

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
1-in-2	Typical Event Day	0.38	0.09	10	84
	May Monthly Peak	0.36	0.09	10	82
	June Monthly Peak	0.15	0.04	4	77
	July Monthly Peak	0.31	0.07	8	82
	August Monthly Peak	0.38	0.09	10	84
	September Monthly Peak	0.49	0.12	12	87
	October Monthly Peak	0.51	0.12	13	86
1-in-10	Typical Event Day	0.45	0.11	12	86
	May Monthly Peak	0.46	0.11	13	86
	June Monthly Peak	0.44	0.11	12	87
	July Monthly Peak	0.44	0.11	12	86
	August Monthly Peak	0.48	0.12	13	86
	September Monthly Peak	0.55	0.13	14	88
	October Monthly Peak	0.50	0.12	12	87

Table 5-2:
Average and Aggregate Load Reductions by Day Type and Weather Year
All Commercial Customers

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
1-in-2	Typical Event Day	0.31	0.08	4.5	81
	May Monthly Peak	0.30	0.08	4.3	80
	June Monthly Peak	0.23	0.06	3.3	75
	July Monthly Peak	0.30	0.08	4.4	81
	August Monthly Peak	0.32	0.08	4.6	81
	September Monthly Peak	0.35	0.09	5.1	85
	October Monthly Peak	0.33	0.09	4.8	83
1-in-10	Typical Event Day	0.34	0.09	5.0	84
	May Monthly Peak	0.32	0.09	4.7	84
	June Monthly Peak	0.33	0.09	4.8	84
	July Monthly Peak	0.33	0.09	4.8	84
	August Monthly Peak	0.35	0.09	5.0	84
	September Monthly Peak	0.37	0.10	5.3	87
	October Monthly Peak	0.34	0.09	5.0	86

Table 5-3:
Average and Aggregate Load Reductions by Day Type and Weather Year
All Customers

Weather Year	Day Type	Average Load Reduction (kW)	Average Load Reduction (kW/Ton)	Aggregate Load Reduction (MW)	Avg. Temp. (°F)
1-in-2	Typical Event Day	0.36	0.09	15	83
	May Monthly Peak	0.34	0.08	14	81
	June Monthly Peak	0.18	0.04	7	77
	July Monthly Peak	0.31	0.08	13	81
	August Monthly Peak	0.36	0.09	15	83
	September Monthly Peak	0.44	0.11	17	87
	October Monthly Peak	0.44	0.11	17	85
1-in-10	Typical Event Day	0.42	0.10	17	86
	May Monthly Peak	0.41	0.10	17	85
	June Monthly Peak	0.40	0.10	17	86
	July Monthly Peak	0.40	0.10	17	85
	August Monthly Peak	0.44	0.11	18	85
	September Monthly Peak	0.49	0.12	19	88
	October Monthly Peak	0.44	0.11	17	87

Figures 5-1 and 5-2 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 2011 enrollment. Figures 5-3 and 5-4 contain the same output tables for commercial customers. Electronic versions of these tables for various day types and weather conditions have been filed along with this report.

Tables 5-4 through 5-6 show how load impacts vary across the five-hour event window for each required ex ante day type and set of weather conditions based on 2011 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 residential customers, for most day types and weather conditions, the largest load impact is in the second to last hour of the event period, from 4 to 5 PM. For commercial customers, impacts in the the 3 to 4 PM interval for both 1-in-2 and 1-in-10 weather year conditions are either equal to or greater than those in the 4 to 5 PM interval.

There are some notable differences in the hourly aggregate load impacts of residential as compared to commercial customers. Residential load impacts are much more varied throughout the 1 to 6 PM event window than are commercial customers. On average the difference between the first hour's load impacts (1 to 2 PM) and the peak hour's load impacts (4 to 5 PM) is 32% in 1-in-2 weather years and 38% in 1-in-10 weather years for residential customers. For commercial customers the difference is much less pronounced between the first hour and the peak hour (3 to 4 PM or 4 to 5 PM) at 9% for both weather year conditions. These differences can be attributed to the different cycling strategies for residential vs. commercial customers (50% and 100% vs. 30% and 50%, respectively), and the energy needs of each group. While residential customers may not use AC while they are out of the house, commercial customers generally need to use AC all day, which stabilizes their projected load impacts.

5.1 Recommendations

FSC has several recommendations for the future:

- Incentive levels should be reviewed for the 100% residential cycling option. It appears that these customers are being overpaid relative to customers on the 50% cycling option;
- The group A-B structure should be retained;
- The residential Summer Saver evaluation should be done using whole-building data, contingent on a validation check to ensure that the group of residential customers with smart meters is adequately representative; and
- An effort should be made to resolve issues with identifying which commercial meters are associated with Summer Saver controlled ACs so that the commercial evaluation can be performed without the need of a load-research sample in the future.

Table 5-4:
Aggregate Load Reductions by Day Type, Weather Year and Hour
All Residential Customers

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	8.7	9.9	10.8	11.6	10.7	10.3
	May Monthly Peak	8.5	9.8	10.5	10.8	9.9	9.9
	June Monthly Peak	3.4	3.8	4.4	4.7	4.2	4.1
	July Monthly Peak	6.8	8.0	8.7	9.3	8.7	8.3
	August Monthly Peak	8.5	9.5	10.4	11.1	10.4	10.0
	September Monthly Peak	10.1	11.9	13.1	13.8	13.0	12.4
	October Monthly Peak	10.6	12.4	13.5	13.8	12.3	12.5
1-in-10	Typical Event Day	10.1	12.1	13.1	13.8	12.8	12.4
	May Monthly Peak	10.2	12.3	13.4	14.0	13.0	12.6
	June Monthly Peak	9.4	11.3	12.6	13.7	12.9	12.0
	July Monthly Peak	9.4	11.2	12.5	13.3	12.3	11.8
	August Monthly Peak	10.6	12.4	13.4	13.8	12.8	12.6
	September Monthly Peak	11.1	13.5	14.4	15.3	14.4	13.7
	October Monthly Peak	9.7	12.2	13.1	13.9	12.7	12.3

Table 5-5:
Aggregate Load Reductions by Day Type, Weather Year and Hour
All Commercial Customers

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	4.4	4.6	4.7	4.7	4.3	4.6
	May Monthly Peak	4.2	4.4	4.5	4.5	4.1	4.3
	June Monthly Peak	3.2	3.4	3.5	3.5	3.1	3.3
	July Monthly Peak	4.2	4.4	4.5	4.5	4.1	4.4
	August Monthly Peak	4.4	4.6	4.8	4.7	4.3	4.6
	September Monthly Peak	4.8	5.1	5.3	5.2	4.9	5.1
	October Monthly Peak	4.5	4.8	5.0	4.9	4.6	4.8
1-in-10	Typical Event Day	4.8	5.0	5.2	5.1	4.7	5.0
	May Monthly Peak	4.4	4.7	4.9	4.9	4.6	4.7
	June Monthly Peak	4.6	4.8	5.0	5.0	4.6	4.8
	July Monthly Peak	4.6	4.9	5.0	5.0	4.6	4.8
	August Monthly Peak	4.9	5.1	5.2	5.2	4.8	5.0
	September Monthly Peak	5.1	5.4	5.5	5.5	5.2	5.3
	October Monthly Peak	4.7	5.0	5.2	5.2	4.8	5.0

Table 5-6:
Aggregate Load Reductions by Day Type, Weather Year and Hour
All Customers

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	13	15	16	16	15	15
	May Monthly Peak	13	14	15	15	14	14
	June Monthly Peak	7	7	8	8	7	7
	July Monthly Peak	11	12	13	14	13	13
	August Monthly Peak	13	14	15	16	15	15
	September Monthly Peak	15	17	18	19	18	17
	October Monthly Peak	15	17	18	19	17	17
1-in-10	Typical Event Day	15	17	19	19	18	18
	May Monthly Peak	15	17	18	19	18	17
	June Monthly Peak	14	16	18	19	18	17
	July Monthly Peak	14	16	18	18	17	17
	August Monthly Peak	15	17	19	19	18	18
	September Monthly Peak	16	19	20	21	20	19
	October Monthly Peak	14	17	18	19	18	17

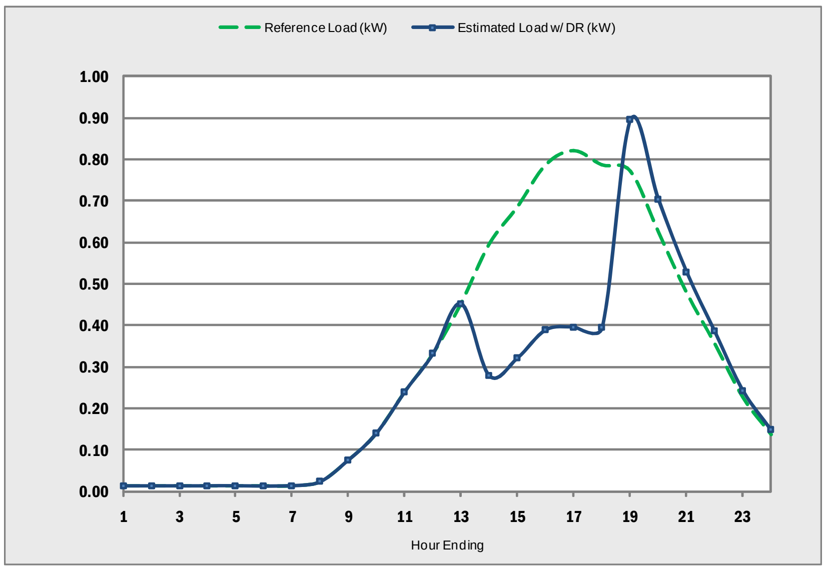
Figure 5-1:
Hourly Load Impact Estimates for the Average Residential AC Unit
Typical Event Day, 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average AC Unit
Weather Year	1-in-2
Forecast Year	2011
Day Type	Typical Event Day
Customer Characteristic	All Residential Customers

TABLE 2: Output

Average Tons per AC Unit	4.2
Aggregate Tons	113,651
% Load Reduction (1 to 6 pm)	51.5%



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	0.01	0.01	0.00	68.5	0.00	0.00	0.00	0.00	0.00
2	0.01	0.01	0.00	68.0	0.00	0.00	0.00	0.00	0.00
3	0.01	0.01	0.00	67.5	0.00	0.00	0.00	0.00	0.00
4	0.01	0.01	0.00	67.1	0.00	0.00	0.00	0.00	0.00
5	0.01	0.01	0.00	66.9	0.00	0.00	0.00	0.00	0.00
6	0.01	0.01	0.00	66.6	0.00	0.00	0.00	0.00	0.00
7	0.01	0.01	0.00	66.7	0.00	0.00	0.00	0.00	0.00
8	0.02	0.02	0.00	71.6	0.00	0.00	0.00	0.00	0.00
9	0.08	0.08	0.00	77.8	0.00	0.00	0.00	0.00	0.00
10	0.14	0.14	0.00	83.0	0.00	0.00	0.00	0.00	0.00
11	0.24	0.24	0.00	86.9	0.00	0.00	0.00	0.00	0.00
12	0.33	0.33	0.00	87.5	0.00	0.00	0.00	0.00	0.00
13	0.45	0.45	0.00	86.5	0.00	0.00	0.00	0.00	0.00
14	0.60	0.28	0.32	85.8	0.29	0.31	0.32	0.33	0.34
15	0.69	0.32	0.36	85.2	0.34	0.35	0.36	0.37	0.39
16	0.79	0.39	0.40	84.5	0.37	0.38	0.40	0.41	0.43
17	0.82	0.40	0.42	82.7	0.40	0.41	0.42	0.43	0.45
18	0.79	0.39	0.39	79.8	0.37	0.38	0.39	0.40	0.42
19	0.77	0.90	-0.12	76.8	-0.15	-0.13	-0.12	-0.11	-0.10
20	0.62	0.70	-0.08	73.8	-0.11	-0.09	-0.08	-0.07	-0.05
21	0.48	0.53	-0.05	71.8	-0.08	-0.06	-0.05	-0.04	-0.03
22	0.36	0.39	-0.03	70.9	-0.06	-0.04	-0.03	-0.02	0.00
23	0.23	0.24	-0.02	69.6	-0.04	-0.03	-0.02	-0.01	0.01
24	0.14	0.15	-0.01	69.3	-0.04	-0.02	-0.01	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	7.63	6.05	1.58	154.7	1.29	1.46	1.58	1.70	1.86

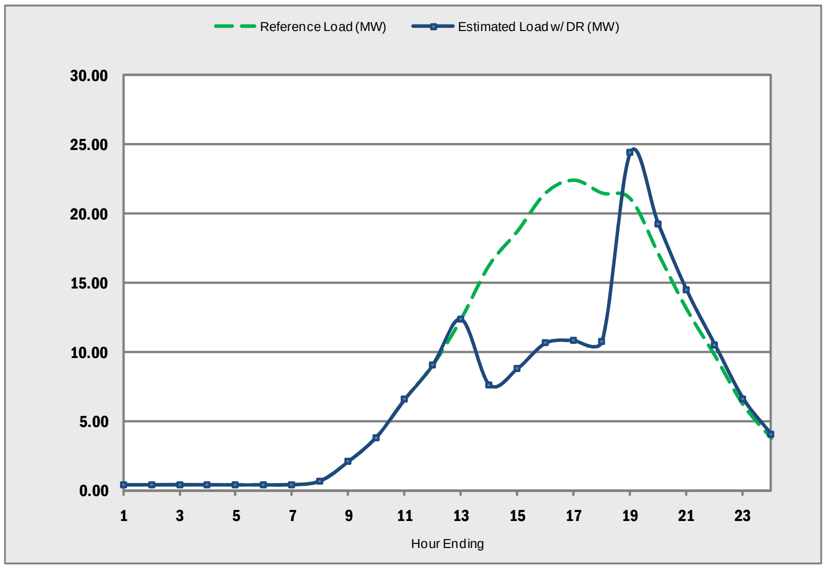
Figure 5-2:
Aggregate Hourly Load Impact Estimates for All Residential Customers
Typical Event Day, 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Aggregate
Weather Year	1-in-2
Forecast Year	2011
Day Type	Typical Event Day
Customer Characteristic	All Residential Customers

TABLE 2: Output

Average Tons per AC Unit	4.2
Aggregate Tons	113,651
% Load Reduction (1 to 6 pm)	51.5%



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	0.38	0.38	0.00	68.5	0.00	0.00	0.00	0.00	0.00
2	0.38	0.38	0.00	68.0	0.00	0.00	0.00	0.00	0.00
3	0.38	0.38	0.00	67.5	0.00	0.00	0.00	0.00	0.00
4	0.38	0.38	0.00	67.1	0.00	0.00	0.00	0.00	0.00
5	0.38	0.38	0.00	66.9	0.00	0.00	0.00	0.00	0.00
6	0.38	0.38	0.00	66.6	0.00	0.00	0.00	0.00	0.00
7	0.38	0.38	0.00	66.7	0.00	0.00	0.00	0.00	0.00
8	0.65	0.65	0.00	71.6	0.00	0.00	0.00	0.00	0.00
9	2.07	2.07	0.00	77.8	0.00	0.00	0.00	0.00	0.00
10	3.84	3.84	0.00	83.0	0.00	0.00	0.00	0.00	0.00
11	6.57	6.57	0.00	86.9	0.00	0.00	0.00	0.00	0.00
12	9.06	9.06	0.00	87.5	0.00	0.00	0.00	0.00	0.00
13	12.37	12.37	0.00	86.5	0.00	0.00	0.00	0.00	0.00
14	16.28	7.61	8.66	85.8	7.94	8.37	8.66	8.96	9.38
15	18.72	8.79	9.93	85.2	9.17	9.62	9.93	10.24	10.68
16	21.48	10.64	10.83	84.5	10.02	10.50	10.83	11.17	11.65
17	22.40	10.83	11.57	82.7	10.90	11.30	11.57	11.84	12.24
18	21.46	10.78	10.68	79.8	9.99	10.39	10.68	10.96	11.37
19	21.05	24.44	-3.38	76.8	-4.08	-3.67	-3.38	-3.10	-2.68
20	17.05	19.23	-2.18	73.8	-2.88	-2.46	-2.18	-1.90	-1.48
21	13.06	14.46	-1.40	71.8	-2.09	-1.68	-1.40	-1.11	-0.70
22	9.71	10.53	-0.82	70.9	-1.51	-1.10	-0.82	-0.54	-0.13
23	6.17	6.64	-0.47	69.6	-1.14	-0.75	-0.47	-0.19	0.20
24	3.75	4.05	-0.30	69.3	-1.00	-0.58	-0.30	-0.02	0.40
	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	208.31	165.20	43.11	154.7	35.32	39.92	43.11	46.30	50.91

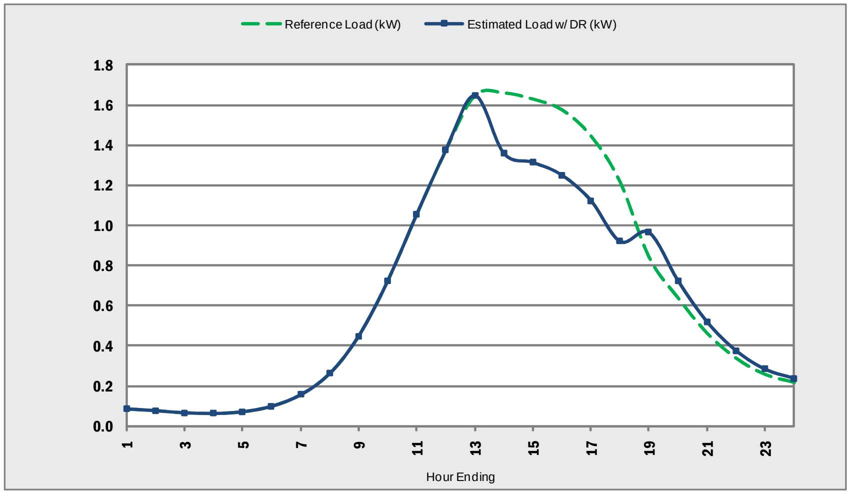
Figure 5-3:
Hourly Load Impact Estimates for the Average Commercial Customer
Typical Event Day, 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average AC Unit
Weather Year	1-in-2
Forecast Year	2011
Day Type	Typical Event Day
Customer Characteristic	All Commercial Customers

TABLE 2: Output

Average Tons per AC Unit	3.8
Aggregate Tons	54,778
% Load Reduction (1 to 6 pm)	20.8%



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	0.09	0.09	0.00	69.0	0.00	0.00	0.00	0.00	0.00
2	0.08	0.08	0.00	68.5	0.00	0.00	0.00	0.00	0.00
3	0.07	0.07	0.00	68.0	0.00	0.00	0.00	0.00	0.00
4	0.06	0.06	0.00	67.6	0.00	0.00	0.00	0.00	0.00
5	0.07	0.07	0.00	67.5	0.00	0.00	0.00	0.00	0.00
6	0.10	0.10	0.00	67.2	0.00	0.00	0.00	0.00	0.00
7	0.16	0.16	0.00	67.4	0.00	0.00	0.00	0.00	0.00
8	0.26	0.26	0.00	71.1	0.00	0.00	0.00	0.00	0.00
9	0.45	0.45	0.00	76.2	0.00	0.00	0.00	0.00	0.00
10	0.72	0.72	0.00	80.7	0.00	0.00	0.00	0.00	0.00
11	1.05	1.05	0.00	84.0	0.00	0.00	0.00	0.00	0.00
12	1.37	1.37	0.00	84.3	0.00	0.00	0.00	0.00	0.00
13	1.65	1.65	0.00	83.8	0.00	0.00	0.00	0.00	0.00
14	1.66	1.36	0.30	83.2	-0.35	-0.32	-0.30	-0.28	-0.26
15	1.63	1.31	0.32	82.8	-0.36	-0.34	-0.32	-0.30	-0.28
16	1.58	1.25	0.33	82.3	-0.37	-0.34	-0.33	-0.31	-0.29
17	1.45	1.12	0.32	80.8	-0.37	-0.35	-0.33	-0.32	-0.29
18	1.22	0.92	0.30	78.3	-0.34	-0.31	-0.30	-0.28	-0.26
19	0.84	0.96	-0.12	75.9	0.08	0.11	0.12	0.14	0.16
20	0.64	0.72	-0.08	73.4	0.04	0.06	0.08	0.10	0.12
21	0.46	0.52	-0.06	71.7	0.01	0.04	0.05	0.07	0.09
22	0.34	0.38	-0.04	71.0	0.00	0.02	0.03	0.05	0.07
23	0.26	0.28	-0.03	70.0	-0.01	0.01	0.03	0.04	0.06
24	0.22	0.24	-0.02	69.5	-0.02	0.00	0.02	0.03	0.06
	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	16.42	15.20	1.22	129.6	-1.69	-1.43	-1.24	-1.06	-0.80

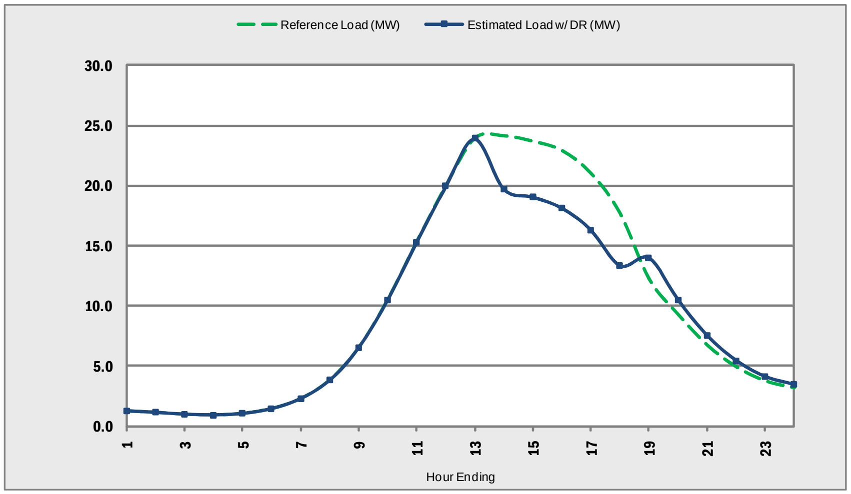
Figure 5-4:
Aggregate Hourly Load Impact Estimates for All Commercial Customers
Typical Event Day, 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Aggregate
Weather Year	1-in-2
Forecast Year	2011
Day Type	Typical Event Day
Customer Characteristic	All Commercial Customers

TABLE 2: Output

Average Tons per AC Unit	3.8
Aggregate Tons	54,778
% Load Reduction (1 to 6 pm)	20.8%



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	1.25	1.25	0.00	69.0	0.00	0.00	0.00	0.00	0.00
2	1.13	1.13	0.00	68.5	0.00	0.00	0.00	0.00	0.00
3	0.97	0.97	0.00	68.0	0.00	0.00	0.00	0.00	0.00
4	0.93	0.93	0.00	67.6	0.00	0.00	0.00	0.00	0.00
5	1.04	1.04	0.00	67.5	0.00	0.00	0.00	0.00	0.00
6	1.44	1.44	0.00	67.2	0.00	0.00	0.00	0.00	0.00
7	2.27	2.27	0.00	67.4	0.00	0.00	0.00	0.00	0.00
8	3.81	3.81	0.00	71.1	0.00	0.00	0.00	0.00	0.00
9	6.51	6.51	0.00	76.2	0.00	0.00	0.00	0.00	0.00
10	10.49	10.49	0.00	80.7	0.00	0.00	0.00	0.00	0.00
11	15.30	15.30	0.00	84.0	0.00	0.00	0.00	0.00	0.00
12	19.94	19.94	0.00	84.3	0.00	0.00	0.00	0.00	0.00
13	23.90	23.90	0.00	83.8	0.00	0.00	0.00	0.00	0.00
14	24.10	19.72	4.39	83.2	-5.01	-4.64	-4.39	-4.13	-3.76
15	23.65	19.06	4.59	82.8	-5.22	-4.86	-4.62	-4.37	-4.01
16	22.88	18.14	4.74	82.3	-5.35	-5.00	-4.75	-4.51	-4.15
17	20.99	16.30	4.69	80.8	-5.42	-5.07	-4.83	-4.59	-4.24
18	17.67	13.35	4.33	78.3	-4.91	-4.56	-4.33	-4.09	-3.74
19	12.22	14.00	-1.78	75.9	1.20	1.54	1.78	2.02	2.36
20	9.27	10.50	-1.22	73.4	0.60	0.93	1.17	1.40	1.74
21	6.72	7.53	-0.81	71.7	0.21	0.55	0.78	1.01	1.35
22	4.92	5.46	-0.54	71.0	-0.06	0.28	0.51	0.74	1.07
23	3.75	4.12	-0.37	70.0	-0.20	0.13	0.37	0.60	0.94
24	3.17	3.46	-0.29	69.5	-0.32	0.01	0.25	0.48	0.82
	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	238.36	220.65	17.71	129.6	-24.49	-20.69	-18.06	-15.43	-11.63