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Load Impact Estimates for SCE's Demand Response Programs:
Residential and Commercial Summer Discount Plan
Agricultural and Pumping Interruptible Program
Real Time Pricing

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1 Executive Summary

This report provides load impact estimates for the following four Southern California Edison (SCE) demand response programs:

- Summer Discount Plan (SDP) program for residential customers;
- SDP program for commercial customers;
- Agricultural and Pumping Interruptible (AP-I) program; and
- Real Time Pricing tariff (RTP).

1.1 Demand Response Load Impact Summary

Three of the four demand response (DR) programs addressed in this report are event-based resources. The SDP resource had two system wide events for both its residential and commercial customers. The AP-I resource had two events in 2010. Ex post load impact estimates are provided for each of these events. For RTP, which is a non-event based program, ex post load impact estimates are developed for the average weekday and monthly system peak day for each month in 2010, as required by the load impact protocols.

Ex ante load impact estimates were developed for the years 2011 through 2021. For each program, ex ante estimates are provided for the average customer and for all enrolled customers under two sets of weather conditions (representing 1-in-2 and 1-in-10 weather years), by CAISO Local Capacity Area (LCA) and forecast year. The number of potential tables containing load impact estimates runs in the thousands. Only selected tables are presented in this report. Electronic copies of spreadsheet models meeting all load impact filing requirements are available.

1.1.1 Summer Discount Plan for Residential Customers

SCE's Summer Discount Plan for residential customers is the Company's second largest DR resource. The load reduction potential derives from the reduction in air conditioning (AC) energy use provided through direct load control devices. There are about 330,000 residential service accounts participating in the SDP program and approximately 380,000 control devices installed.

The ex post analysis examined one system-wide event from 3:16 PM to 6:13 PM on September 27th. The event generated an average aggregate load reduction of 743 MW with an average per customer impact of 2.2 kW during the event. The average reference load per customer during the event was 2.6 kW. Residential load impacts are very high compared to reference loads for two reasons. First, reference loads are AC load, not whole-building load. Second, the majority of residential customers are on the 100% cycling option, which reduces load to zero during an event.

For the forecast year 2011, in a normal weather year (e.g., 1-in-2), on a typical event day, the estimated load impact per residential customer during the event is 1.5 kW, with an average aggregate impact of 457 MW. Based on 1-in-10 year weather conditions, the average load impact across the four hours is 1.7 kW, with an average aggregate impact of 532 MW. Enrollment forecasts were provided by SCE.

Residential load impacts on September 27th significantly exceeded all ex ante impacts for two reasons. First, the temperature was hotter on that day than on any ex ante day. September 27th temperatures peaked at about 104°F and remained above 100°F for several hours in the middle of the day. Ex ante conditions for a typical event day peak in the mid-90s. Second, the event on September 27th was almost perfectly timed to capture residential peak AC loads, which translated into large impacts. Ex ante event impacts are predicted for a window of time over which residential reference loads start fairly low and grow towards the end of the event.

1.1.2 Summer Discount Plan for Commercial Customers

The SDP for commercial customers is similar to the SDP program for residential customers. Customers receive a credit on their summer season electric bills and in return SCE has the option to cycle the customer's AC compressor. Customers served under the following tariffs are eligible for the commercial SDP program: GS-1, TOU-GS-1, GS-2, TOU-GS-3 and TOU-8. There are about 11,000 commercial accounts enrolled in the program. The total number of control devices installed on these accounts is approximately 73,000. This is a substantial increase in enrollment from January 2006, when there were fewer than 2,500 commercial accounts enrolled.

The ex post analysis examined two system-wide events: a 30-minute event on July 29th and a 3-hour event on September 27th. The July 29th event generated a peak of 7.1 MW of aggregate load reduction in the first half hour, with an average impact per AC unit of 0.1 kW. The September 27th event generated an average aggregate load reduction of 46 MW, with an average impact per AC unit of 0.9 kW. The average reference load during the event was 1.9 kW per AC unit.

On a per AC unit basis, the average residential SDP reference load during the September 27th event was 2.3 kW, roughly 20% higher than the per AC unit commercial reference load. The primary reason for this is that the event occurred fairly late in the day. That means that the event just caught the tail of the commercial load peak, while occurring right in the middle of the residential load peak. Average commercial load drops off dramatically during the event, while residential load stays high throughout. In fact, peak commercial reference load per AC unit on September 27th is virtually identical to peak residential reference load, at 2.4 kW. However, the commercial peak takes place just before the event, at 3 PM, while the residential peak occurs during the hours 4 PM to 6 PM. Average AC tonnage and temperatures experienced during the event are very similar between the groups.

Commercial load impacts as a percentage of reference load are smaller than residential load impacts as a percentage of reference load because a greater proportion of commercial customers have chosen the 30% and 50% cycling options instead of the 100% option. Only about 60% of commercial customers have chosen the 100% option, as compared to 90% of residential customers.

Commercial ex ante load impacts for 2011 under 1-in-10 year weather conditions follow a similar pattern as the impacts in a 1-in-2 weather year, but are higher due to the higher amount of AC load and higher duty cycles. For the typical event day, the average AC unit load impact over the same event window is 1.0 kW, or 20% higher than the typical event day in a 1-in-2 weather year. In aggregate, the commercial SDP program provides approximately 51 MW of load relief on a typical event day under 1-in-2 year weather conditions. For 1-in-10 year weather conditions, the aggregate load drop for a typical event day equals 59 MW. As for residential customers, commercial enrollment forecasts were provided by SCE.

1.1.3 Agricultural and Pumping Interruptible Program

The Agricultural and Pumping Interruptible (AP-I) program provides a monthly credit to eligible agricultural and pumping customers for allowing SCE to temporarily interrupt electric service to their pumping equipment during CAISO or other system emergencies. As of September 2010, 802 customers were enrolled in the program. Enrollment is highest in the Ventura LCA, where 533 customers are enrolled. The second largest region in terms of enrollment is the LA Basin LCA, with 198 participants, followed by the Outside LA Basin LCA, with 71 participants.

In 2010, an AP-I event was called for the first time since November 2008. There were two AP-I events in total. The first event was on July 29th and lasted from 6:57 PM to 7:28 PM. It generated an average load drop of 50.7 kW per participant and 39.7 MW on aggregate. The second 2010 event was on September 27th from 3:16 PM to 4:31 PM. It generated an average load drop of 33.8 kW per participant and an aggregate load drop of 27.1 MW.

Ex ante load impact estimates were developed for the years 2011 through 2021. Once enrollment and the switch success rate reach their expected steady state in the 2015 to 2021 time period, the program is projected to be capable of delivering up to 58 MW of load reduction, which occurs during the May monthly peak under 1-in-10 weather conditions. If SCE reaches its forecast target of a 95% switch success rate by August 2014, the aggregate 1-in-2 load impact is 46.6 MW and the 1-in-10 result is 48.5 MW.

1.1.4 Real Time Pricing

The Real Time Pricing (RTP) program is a dynamic pricing tariff that charges participants for the electricity they consume based on hourly prices that vary according to day type and temperature. It attempts to incorporate both the time-varying components of energy costs and generation capacity costs. The RTP tariff consists of nine hourly pricing profiles that vary by season, day type and a range of temperatures measured at the Los Angeles Civic Center on the previous day. The tariff is available to large commercial and industrial customers (i.e., customers eligible for service under Schedule TOU-8). Because the rate schedules are linked to variation in weather, participants experience more high-price days during extreme weather years than in normal weather years.

For the ex post analysis, the overall impacts were calculated as the difference between regression-predicted load under 2010 RTP prices and under the Otherwise Applicable Tariff (OAT). Impacts were estimated for each monthly system peak day in 2010. The largest estimated impact occurred on September 27, 2010, which generated an average load drop of 196.6 kW and an aggregate load drop of nearly 20 MW during the peak period from 1 PM to 6 PM. This represents a 15.5% reduction relative to the aggregate reference load of 127 MW.

Ex ante load impact estimates were developed for the years 2011 through 2021. Once enrollment reaches its expected steady state in August 2014, the program is projected to be capable of delivering 40.1 MW of load reduction on the days with the highest RTP prices, which occur during September under

1-in-2 system conditions and June, August and September in a 1-in-10 weather year. SCE system load typically peaks during August and September. For these monthly peaks in a 1-in-2 and 1-in-10 weather year, aggregate impacts are expected to double from 2011 to 2014 as a result of new enrollment.

1.2 Report Structure

The remainder of this report contains one section for each of the four DR resources described above. The residential and commercial SDP load impact estimates are presented in Sections 2 and 3. Impact estimates for the AP-I and RTP programs are contained in Sections 4 and 5. Each section provides a brief overview of the program objectives, history and current enrollment values. This is followed by a discussion of analysis methodology, including an assessment of the validity of the models and estimates. The remainder of each section presents the analysis results and provides recommendations for future evaluations.

2 Residential Summer Discount Plan

2.1 Plan Overview

SCE's Summer Discount Plan for residential customers (residential SDP) is the company's second largest demand response (DR) resource after the Base Interruptible Program. The program's load reduction potential derives from the reduction in AC energy use provided through direct load control devices, which restrict the amount of time AC units are allowed to operate per hour. SDP is an emergency resource. Load control events may be called under three circumstances:

- When the California Independent System Operator (CAISO) notifies SCE that they must reduce a certain amount of electrical load on the system. The CAISO can call for load reduction events at any time during the summer, 24 hours a day, 7 days a week, including holidays;
- Upon determination by SCE's grid control center of the need to implement load reductions in SCE's service territory; or
- When SCE activates a test event. One test event may be called in each summer season. If warranted, SCE may also call a second 30-minute test event to validate operating systems. Test events do not require any specific system conditions before activation.

SDP customers have several options they can choose from regarding the frequency of interruption and the percent of time that cycling can occur. The primary options are:

- The Base Summer Discount Plan (APS), which allows SCE to control AC units a maximum of 15 times (up to 6 hours per time, multiple times per day if necessary) during the summer season;
- The Enhanced Summer Discount Plan (APS-E), which allows SCE to control ACs for an unlimited number of days per year (up to six hours per time) during the summer season; or
- Choice of cycling. Residential customers can currently choose from two cycling rates: 50% (AC disconnected for 15 minutes out of every 30 minutes), and 100% (AC disconnected continuously during the cycling event). In addition, 7.1% of AC units are enrolled in 67% cycling (AC disconnected for 20 minutes out of every 30 minutes), an option that has been discontinued.

Table 2-1 shows the fraction of residential customers by LCA and their chosen cycling strategy. For residential customers, 91% of the installed devices were on 100% cycling while 7% were on the 67% cycling option and the remaining 2% were on 50% cycling.

Table 2-1:
Fraction of Customers by Cycling Strategy and LCA From SDP Residential Population

Local Capacity Region	Cycling Strategy (% of units)			Total
	50%	67%	100%	
LA Basin	1.7	5.6	68.7	76.0
Outside LA Basin	0.2	0.5	9.1	9.8
Ventura	0.3	0.9	12.9	14.2
Total	2.2	7.1	90.7	100.0

In exchange for allowing SCE to control their AC units, participants receive a bill credit during the entire summer season. The Enhanced Plan provides twice the credit as the Base Plan. Within each plan, the bill credit is proportional to the number of AC tons enrolled in the program and increases with the cycling percentage. For residential customers, the incentive payment ranges from a low of $0.05/ton of AC per day for the Base Plan and a 50% cycling strategy to a high of $0.36/ton for the 100% cycling strategy and unlimited interruptions. Over the course of the four-month summer from June 1st to October 1st, for a household with a 3-ton AC unit, the incentive would range from a low of roughly $18 for the Base Plan and a 50% cycling strategy to a high of almost $130 for the 100% cycling strategy and unlimited interruptions.

Participation in SDP has experienced steady growth over the past few years. The total number of residential participants has increased from 125,000 accounts in January 2005 to 343,000 accounts by the end of June 2010. The LA Basin local capacity area (LCA) contains the largest number of service accounts (260,000). The Ventura LCA has approximately 48,000 enrolled customers and the remaining participants are located in the Outside LA Basin LCA.

Ex post impact estimates are provided for the September 27th 2010 event. These impacts are calculated by taking the September 27th, 2010 weather data and estimating the reference load using a regression model of load developed for AC usage among a 2005-2007 residential sample for which AC logger data was collected. Percent impacts are then imputed using percent impacts determined from a load research sample from a neighboring utility, San Diego Gas & Electric Company (SDG&E). These steps were necessary to produce impact estimates, because no new data were collected for the residential population of SDP participating in 2010.

Ex ante load impact estimates have been produced for each year for 2011 through 2021. Estimates are provided for each of the three LCAs in SCE's service territory as well as for all customers combined. The ex ante impacts reflect the load reduction capability of the program under a standard set of 1-in-2 and 1-in-10 year weather conditions.

Impact estimates for commercial SDP are based on a sample of AC logger data collected during the summer of 2010, while results for residential SDP are based on a sample of AC logger data collected during 2005-2007. The analyses are somewhat different and therefore they are described in separate sections.

2.2 Selection of Analysis Methodology

The dataset used for analysis of residential SDP loads and impacts is the same as that used for the 2009 evaluation. In order to avoid unnecessary duplication of effort, the 2009 statistical model is retained. The model is used to predict impacts for the September 27th event and for the ex ante weather conditions. The only reason the ex ante analysis has changed since 2009 is the need in 2010 to predict for a 1 PM to 6 PM event window. In 2009, the event window for ex ante was 2 PM to 6 PM.

The SDP, and its predecessor program, the Air Conditioning Cycling Program (ACCP), have been in place for many years and there have been a relatively large number of events over that history. However, most events are localized and do not cycle the entire customer population. In 2005, Edison drew a proportional, random sample of participating residential customers and placed interval meters on the AC units associated with these households. The initial sample was designed to meter 100 households that had enrolled in the program prior to 2004, and 50 households that had enrolled in 2004. The sample was stratified by plan (Base or Enhanced), cycling percentage (100%, 67% or 50%) and climate region. The actual distribution of customers for which data became available included 94 households that had participated prior to 2004 and 53 households that joined in 2004 giving a total of 147 households and 166 AC units. For 2005, interval data were only available for a subset of units, with most meters capturing only part of the 2005 summer months. For the 2006 and 2007 summer months, interval data were available for the full sample.

Although the estimating sample consisted of program participants, control events were called for only a few customers during the period of time over which data were collected. As such, it is not possible to estimate impacts based on actual events using the residential AC logger data.

The methodology used to estimate load impacts in this report is the same as the approach used for the 2009 evaluation, but different from the approach that was used in prior evaluations.[1] In prior evaluations, load impacts were estimated using the following four-stage process:

1. Develop a regression model based on historical data of actual participant behavior;
2. Estimate the reference load for the 1-in-2 and 1-in-10 year weather conditions using the regression models estimated in step 1 and ex ante values for the explanatory variables such as weather, time-of-day and day-of-week variables, etc.;
3. Estimate the load impact as a percentage reduction from the reference load based on cycling strategy and duty cycle analysis; and
4. Adjust the impacts based on switch/communication success rate.

While this approach was appropriate given the available data, it has two shortcomings. First, it is based on the assumption that there is consistency between the amount of total AC load that is captured by the control device and the end-use logger data used in the sample of customers for which AC load data was collected. ACs use electricity to run both compressors and fans and these two motors run separately. For example, the indoor fan often runs when the compressor is off (although the opposite is never true).

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[1] See Stephen S. George and Josh Bode. *Load Impact Estimates for SCE's Demand Response Programs: Residential and Commercial Summer Discount Plan Agricultural and Pumping Interruptible Program Real Time Pricing Optional Binding and Mandatory Curtailment*, Final Report May 1, 2009. Section 3.3.

The load control device installed by SCE controls the compressor but not the indoor fan load, while the data loggers capture both devices. Given this, it is not correct to set the estimated load impact for the load control device for 100% cycling equal to the full value of the reference load measured by the end-use loggers.

Another challenge in using the available SCE data is that the relationship between load drop and AC cycling strategy is not linear even when only compressor load is measured, since AC duty cycles affect the percent load reduction obtainable at various temperatures. For example, if the ACs duty cycle at a particular temperature is 50%, a 100% cycling strategy will reduce compressor load by 100%, but a 50% cycling strategy may provide little or no load reduction. This happens because the AC can run during the 15 minutes in each half hour that it is not being controlled by the load control switch. Furthermore, when the fan load is not controlled, the relationship between duty cycle, cycling strategy and temperature is even more complex. Fan load comprises a larger share of total unit load at lower temperatures when compressor duty cycles are low; as compared at higher temperatures when the duty cycle is much greater. Given these complexities, actual measured event impacts produce more robust estimates of percent load reductions than simple assumptions or engineering calculations.

In light of the factors outlined above, the load impact estimates presented here are based on reference loads estimated using the SCE sample and average percent load reductions borrowed from San Diego Gas and Electric Company's load research sample. The SDG&E percent impacts are based on actual event data for six events in 2009. Although impact estimates from 2010 were developed for the SDG&E sample, the 2009 SDG&E event weather covered a broader range of temperatures and a range closer to the relevant range for SDP. To the degree that Summer Saver 2010 impacts took place under similar weather conditions, they were comparable with the 2009 impacts. Therefore 2009 impacts are used here. The 67% cycling values are interpolated from the 50% and 100% data, as SDG&E did not have a 67% cycling option in its program.

Table 2-2 shows the percent load reductions by cycling strategy and temperature bin that were obtained from the SDG&E sample. As seen, even at high temperatures, a 100% cycling strategy only produces roughly an 88% drop in total AC load. The 12% difference between the cycling strategy and the load drop is a function of activation failures (due to either communication or equipment failure) and the percent of total AC load that is accounted for by the fan. At lower temperatures and lower cycling strategies, the fan load is a much larger share of total AC energy use. This analysis assumes that activation failures and fan loads are similar between the SCE sample and the SDG&E load research sample.

Table 2-2:
Percent Load Reductions by Cycling Strategy and Temperature Bin From SDG&E Load Research Sample

Temperature (°F)	Cycling Option		
	50%	67%	100%
<85	38	47	72
85-90	39	50	79
90-95	42	54	88
95+	43	51	88

2.2.1 Regression Model Development, Specification and Parameters

A panel-regression model of AC load was used to predict reference loads as a function of the time of day, day of week, temperature and location of the customer.

Table 2-3 shows how many devices are in the estimating sample by LCA and cycling option. As shown, the current estimation sample contains few devices in the Outside LA Basin LCA. A panel regression allows for the averaging of temperature effects across LCAs so that a few customers do not skew the predicted results for an entire LCA.

Table 2-3:
Devices by Cycling Strategy and LCA From SCE Residential Sample

LCA	Cycling Option			
	50%	67%	100%	Total
LA Basin	2	11	102	115
Outside LA Basin	0	0	11	11
Ventura	0	2	38	40
Total	**2**	**13**	**151**	**166**

The regression model estimates AC load as a function of temperature variables and customer- and time-specific indicator variables. These indicator variables allow average AC load to respond differently to weather for different customers at different times. For example, a typical customer's AC use is different for high temperatures at noon on Saturday than at noon on Tuesday. Similarly, AC load at a particular temperature and time will vary between a customer with a larger AC and a customer with a smaller unit. The regression model allows for such differences.

The final model employed was a panel regression with fixed effects. A fixed effect means that the model identifies an average use level for each customer. The regression then uses the independent variables to best fit load shapes around that average. Several model specifications were tested. The chosen model did the best overall job at in-sample and out-of-sample prediction. The dependent variable in the model is hourly energy use for an AC unit. Mathematically, the regression can be expressed by:

$$
\begin{aligned}
kW_{xt} &= a_x + b^{CDH_t} * CDH_t + b^{CDH_t \wedge 2} * CDH_t \wedge 2 + \sum_{x=0}^{3} b^{CDH_{t-x}} CDH_{t-x} \\
&+ \sum_{x=0}^{3} b^{CDH_{t-x} \wedge 2} (CDH_{t-x}) \wedge 2 + b^{CL*CDH} CL_t * CDH_t + b^{(CL*CDH) \wedge 2} (CL_t * CDH_t) \wedge 2 \\
&+ \sum_{i=6}^{9} b^{CDH*month_i} CDH_t * month_i + \sum_{i=6}^{9} b^{(CDH*month_i) \wedge 2} (CDH_t * month_i) \wedge 2 \\
&+ \sum_{i=2}^{7} b^{CDH*dayofweek_i} CDH_t * dayofweek_i \\
&+ \sum_{i=2}^{7} b^{(CDH*dayofweek_i) \wedge 2} (CDH_t * dayofweek_i) \wedge 2 \\
&+ \sum_{i=2}^{24} b^{\ln(NightCDH*hour_i)} * \ln(NightCDH_t) * hour_i
\end{aligned}
$$

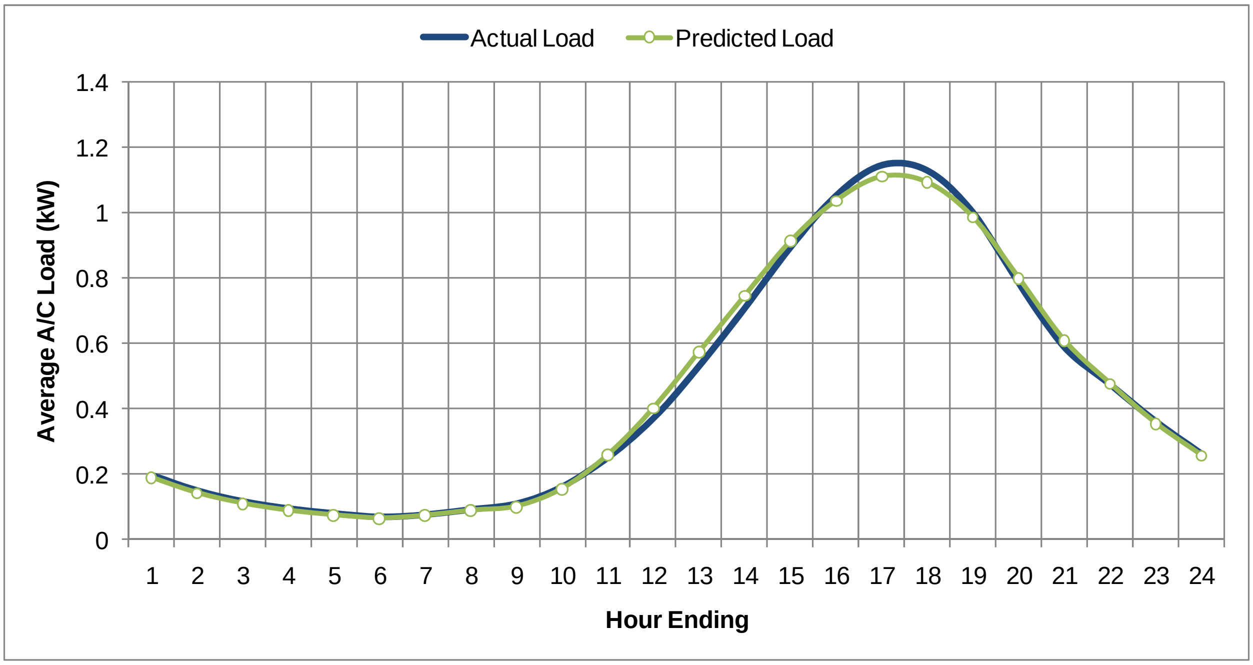
Table 2-4:
Description of the Regression Variables

Variable	Description
kW_{tx}	represents hourly AC load for customer x at time t
a_x	is the overall average AC level for customer x
b's	estimated parameters
CDH_{t-x}	number of cooling degree hours (base 65) at time t-x
CL_t	connected load (kW) of the AC unit;
$NightCDH_t$	sum of cooling degree hours (base 65) from midnight to 6 AM
$Month_i$	indicates a series of binary variables representing each month of the summer (6-9)
$Dayofweek_i$	indicates a series of binary variables representing each day of the week (1-7)
$Hour_i$	indicates a series of binary variables representing each hour of the day (1-24)
e_t	an error term

2.2.2 Model Accuracy and Validity Assessment

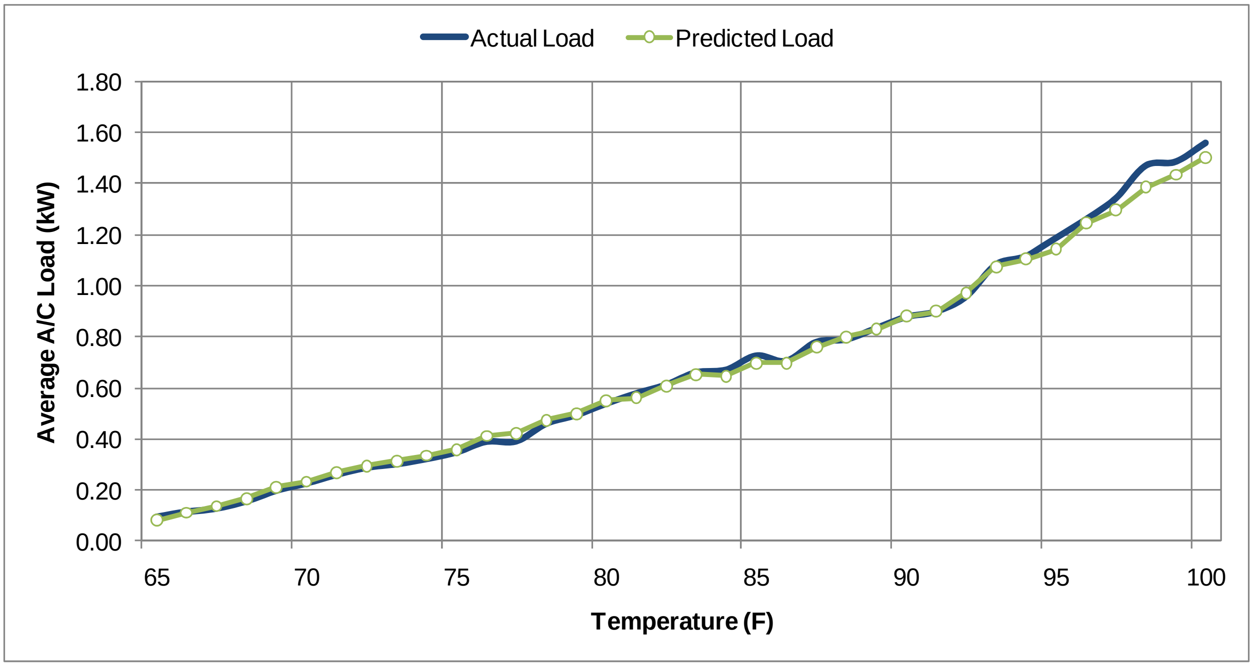
The model accurately predicts load under various weather conditions and for each hour of the day. Figure 2-1 shows the average actual and predicted load on weekdays by hour of the day. The model is quite accurate. Figure 2-2 shows the actual and predicted average values across all sample customers at various temperature levels.

Figure 2-1:
SDP Residential Comparison of Actual and Regression Predicted Load Average Summer Weekday by Hour



Note that in both figures, the model's predictions deviate somewhat from actual loads when temperatures are hottest (in the middle of the afternoon in Figure 2-1). This happens for two reasons. First, the amount of data available at the very hottest temperatures is smaller than at more moderate temperatures. Second, due to heterogeneity in usage across customers and across different operating conditions, it is difficult to find a specification that both fits all available data very well and is reliable for out-of-sample prediction. Forcing the model to fit all data perfectly through the use of many covariates can lead to unstable results in out-of-sample predictions.

Figure 2-2:
SDP Residential Comparison of Actual and Regression Predicted Load
All Summer Hours by Temperature

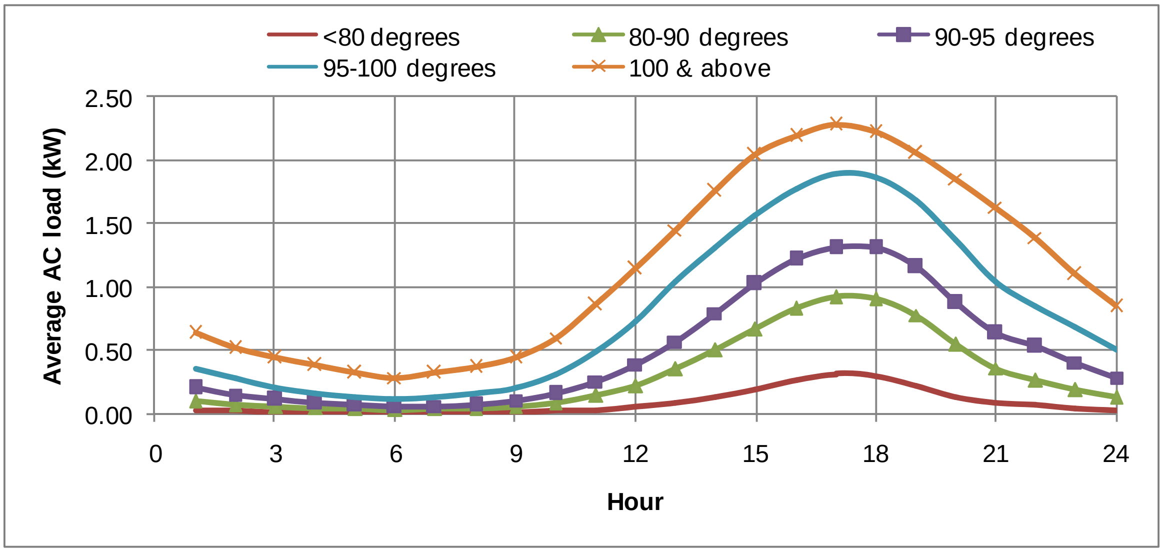


2.3 Air Conditioner Load Patterns

AC load is highly sensitive to weather and occupancy patterns. Extreme system conditions coincide with higher AC loads and therefore higher SDP residential load reduction potential. However, AC load varies substantially with weather conditions, making it critical to accurately predict the amount of AC load available for reduction on any particular day.

Figure 2-3 illustrates the sensitivity of AC load to weather conditions by looking at average hourly AC load daily maximum temperature. It reflects actual AC load, weighted to reflect the SDP residential population. The peak AC demand is almost twice as high on a day with a maximum temperature between 95°F and 100°F than on a day with a maximum temperature between 80°F and 90°F. On a day that exceeds 100°F, peak AC load is nearly two and a half times larger.

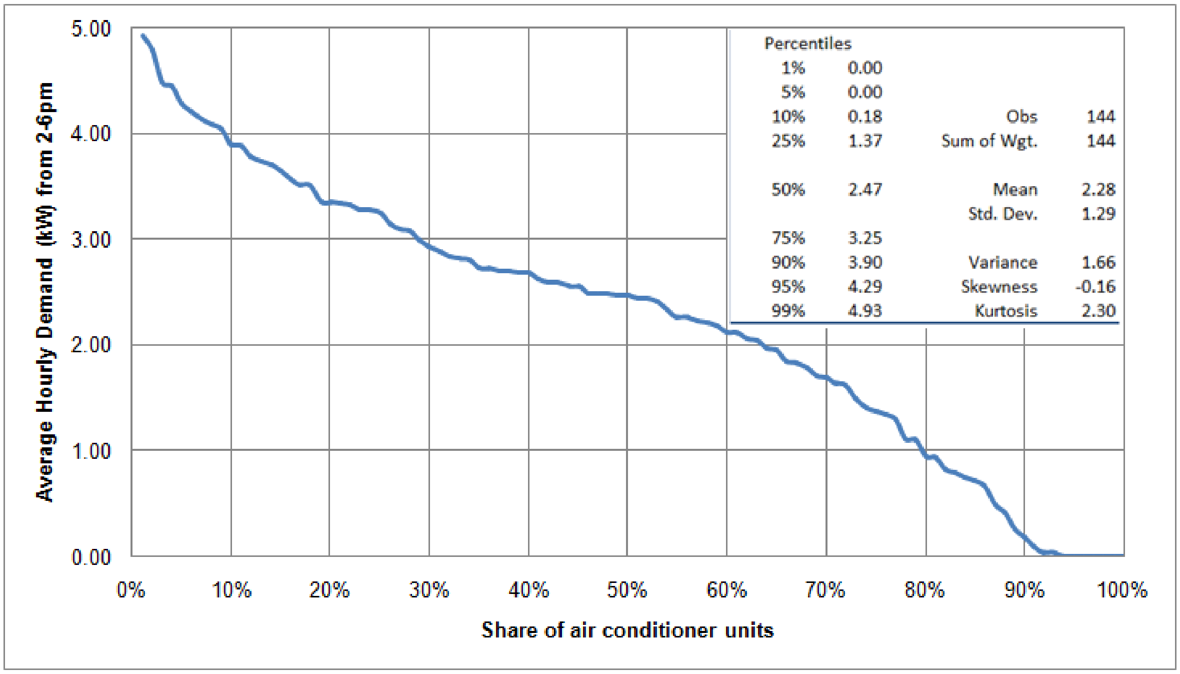
Figure 2-3:
Hourly Average Air Conditioner Load for SDP Residential Customers by Daily Maximum Temperature



For any particular day, the distribution of AC load across participants varies due to occupancy, unit size, comfort thresholds and thermostat settings. The coincidence of AC loads with the highest system load days is closely related to program cost-effectiveness. Identifying heavy versus low users during these hours can aid in targeting customers likely to provide substantial load reduction when an event is called. However, it is not feasible to entirely avoid customers with low or no AC use during critical hours, particularly since hourly load data is not available for each participant. SCE has aligned incentives with AC unit size. Without interval load, it may not be feasible to further align incentives with actual AC use. However, the installation of smart meters will make it possible to design incentive mechanisms that better align with performance. Once participants are enrolled, costs for recruitment installation and equipment are sunk, and the relevant question is whether or not they are cost-effective to retain them in the program.

Figure 2-4 shows the cumulative distribution of the sample load per AC unit during the top-10 system load days between the hours of 2 PM to 6 PM, weighted for the SDP residential participant population. Over 60% of the units exceed 2 kW in AC load. Nearly 30% of participant AC units have 3kW or more in potential load reduction. Figure 2-4 also shows that almost 10% of units register no load during event like conditions, indicating that a tenth of participants receive incentives, yet provide little load reduction.

Figure 2-4:
Distribution of AC Load Coincident with Top-10 System Load Days Critical Hours (2-6 PM)



2.4 Ex Post Impact Estimates

On September 27th, 2010 SCE held a system wide event from 3:16 PM to 5:31 PM for APS customers and from 3:16 PM to 6:13 PM for APS-E customers. Load impacts for this event were estimated at the hourly level using the model and data employed for the 2009 evaluation. The event impacts for the September 27th event were calculated by generating predictions of reference load using the weather data from September 27th, 2010 and assigning impact values from the SDG&E impact results in Table 2-2. The estimated impacts for the September 27th event are shown in Figure 2-5. The event on July 29th was not modeled due to the need to completely re-build the model in order to estimate the effect of a half-hour event.

September 27th was an extremely hot day, with an average temperature of 101°F during the event and sustained temperatures of 104°F in the hours leading to the event. Load impacts per customers peaked at 2.2 kW in the second hour of the event (4 PM), with a reference load of 2.7 kW. Load impacts during the event averaged 83% of reference load. Load impacts were fairly steady during the event such that the average event impact over the three hour event window was 2.2 kW—the same value as the peak impact to within rounding error. The average aggregate load reduction was 743 MW.

Figure 2-5:
Hourly Load Impacts for the Average Residential SDP Customer on September 27th, 2010

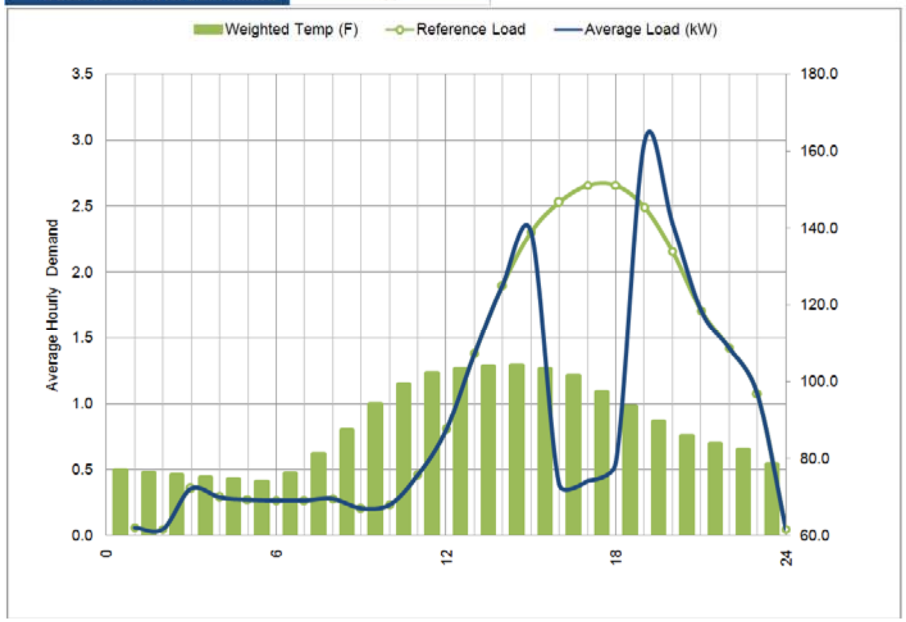
Type of Results	Average Customer
Local Capacity Area	All Customers
Event	September 27th
Year	2010

Local Capacity Region	% of units	Avg Connected Load
LA Basin	76	4.36
Outside LA Basin	10	4.36
Ventura	14	4.36

Local Capacity Region	Cycling Strategy (% of units)			
	50%	67%	100%	TOTAL
LA Basin	1.7	5.6	68.7	76.0
Outside LA Basin	0.2	0.5	9.1	9.8
Ventura	0.3	0.9	12.9	14.2
TOTAL	2.2	7.1	90.7	100.0

TABLE 2: Event Day Information

Event Start	3:16 PM
Event End	6:13 PM
TOTAL ENROLLED ACCOUNTS	343,566
Avg. Load Reduction for Event Window	2.16
% Load Reduction for Event Window	83



Hour Ending	Average Load w/o DR (kW)	Average Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	0.06	0.06	0.00	0.0%	77.1	-0.01	-0.01	-0.01	-0.01	-0.01
2:00	0.05	0.05	0.00	0.0%	76.5	-0.02	-0.02	-0.02	-0.02	-0.02
3:00	0.35	0.35	0.00	0.0%	75.7	-0.04	-0.04	-0.04	-0.04	-0.04
4:00	0.29	0.29	0.00	0.0%	75.1	0.03	0.03	0.03	0.03	0.03
5:00	0.27	0.27	0.00	0.0%	74.5	-0.03	-0.03	-0.03	-0.03	-0.03
6:00	0.27	0.27	0.00	0.0%	73.9	-0.03	-0.03	-0.03	-0.03	-0.03
7:00	0.27	0.27	0.00	0.0%	76.2	-0.03	-0.03	-0.03	-0.03	-0.03
8:00	0.28	0.28	0.00	0.0%	81.3	-0.04	-0.04	-0.04	-0.04	-0.04
9:00	0.21	0.21	0.00	0.0%	87.3	-0.04	-0.04	-0.04	-0.04	-0.04
10:00	0.24	0.24	0.00	0.0%	94.3	-0.05	-0.05	-0.05	-0.05	-0.05
11:00	0.46	0.46	0.00	0.0%	99.3	-0.07	-0.07	-0.07	-0.07	-0.07
12:00	0.80	0.80	0.00	0.0%	102.2	-0.10	-0.10	-0.10	-0.10	-0.10
13:00	1.37	1.37	0.00	0.0%	103.2	-0.15	-0.15	-0.15	-0.15	-0.15
14:00	1.90	1.90	0.00	0.0%	103.8	-0.20	-0.20	-0.20	-0.20	-0.20
15:00	2.30	2.30	0.00	0.0%	104.1	-0.24	-0.24	-0.24	-0.24	-0.24
16:00	2.53	0.39	2.14	84.6%	103.3	1.87	1.87	1.87	1.87	1.87
17:00	2.66	0.41	2.24	84.4%	101.5	1.97	1.97	1.97	1.97	1.97
18:00	2.66	0.55	2.10	79.2%	97.3	1.83	1.83	1.83	1.83	1.83
19:00	2.49	2.99	-0.50	-20.0%	93.5	-0.75	-0.75	-0.75	-0.75	-0.75
20:00	2.15	2.37	-0.22	-10.0%	89.5	-0.44	-0.44	-0.44	-0.44	-0.44
21:00	1.70	1.70	0.00	0.0%	85.9	-0.17	-0.17	-0.17	-0.17	-0.17
22:00	1.42	1.42	0.00	0.0%	83.9	-0.14	-0.14	-0.14	-0.14	-0.14
23:00	1.08	1.08	0.00	0.0%	82.3	-0.11	-0.11	-0.11	-0.11	-0.11
0:00	0.05	0.05	0.00	0.0%	78.5	-0.02	-0.02	-0.02	-0.02	-0.02
	Reference Energy Use w/o DR (kWh)	Predicted Energy Use w/ DR (kWh)	Change in Energy Use (kWh)	% Daily Load Change	Cooling Degree Hours (Base	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	25.85	20.08	-5.77	-22.3%	140.7	-5.8	-5.8	-5.8	-5.8	-5.8

2.5 Ex Ante Impact Estimates

Ex ante load impact values are substantially lower than the impact due to the September 27th event due both to differences in temperature and the difference in event time. The September 27th event was hotter than the ex ante conditions. For example, the 1-in-10 August peak day has a high temperature of 99°F, while September 27th reached 104°F. Also, the event period for ex ante prediction is earlier in the day, which means that much of it misses the residential peak period. The September 27th event was concentrated almost perfectly on the residential peak AC load period.

Figures 2-6 and 2-7 show the estimated reference load and predicted load with demand response for an average customer for the typical ex ante event day based on 1-in-2 and 1-in-10 year weather conditions. In a normal weather year (e.g., 1-in-2 year weather conditions), on a typical event day, the estimated load impact climbs from 1.0 kW in the first event hour to 1.8 kW in the fourth hour. The average load drop over the five hour event period equals 1.5 kW, which is 80% of the average reference load.

Based on 1-in-10 year weather conditions, the load impact pattern over the five-hour period is higher than that of a 1-in-2 weather year due to higher predicted reference loads. Load impacts rise from 1.2 kW from 1 to 2 PM to 2.1 kW from 4 to 5 PM. The average load impact across the four hours is 1.7 kW, which is 80% of average customer load. Residential load impacts on September 27th significantly exceeded all ex ante impacts for two reasons. First, the temperature was hotter on that day than on any ex ante day. September 27th temperatures peaked at about 104°F and remained above 100°F for several hours in the middle of the day. Ex ante conditions for a typical event day peak in the mid-90s. Second, the event on September 27th was almost perfectly timed to capture residential peak AC loads, which translated into large impacts. Ex ante event impacts are predicted for a window of time over which residential reference loads start fairly low and grow towards the end of the event.

Figure 2-6:
Hourly Load Impacts for the Average Residential SDP Customer on a Typical Event Day
1-in-2 Year Weather

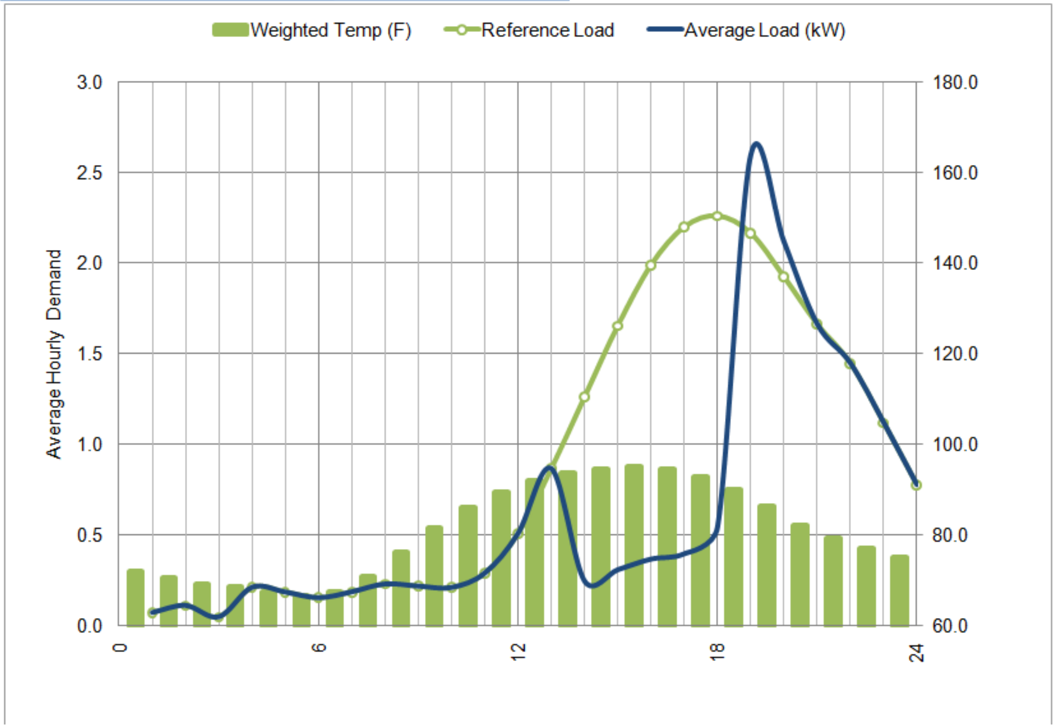
Type of Results	Average Customer
Local Capacity Area	All Customers
Day type	Typical Event Day
Weather Year	1-in-2

Local Capacity Region	% of units	Avg Connected Load
LA Basin	76	4.36
Outside LA Basin	10	4.36
Ventura	14	4.36

Local Capacity Region	Cycling Strategy (% of units) 50%	67%	100%	TOTAL
LA Basin	1.7	5.6	68.7	76.0
Outside LA Basin	0.2	0.5	9.1	9.8
Ventura	0.3	0.9	12.9	14.2
TOTAL	2.2	7.1	90.7	100.0

TABLE 2: Event Day Information

Event Start	1:00 PM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	343,566
Avg. Load Reduction for Event Window	1.50
% Load Reduction for Event Window	80



Hour Ending	Average Load w/o DR (kW)	Average Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)
1:00	0.07	0.07	0.00	0.0%	72.1
2:00	0.11	0.11	0.00	0.0%	70.8
3:00	0.05	0.05	0.00	0.0%	69.4
4:00	0.21	0.21	0.00	0.0%	68.6
5:00	0.19	0.19	0.00	0.0%	67.5
6:00	0.16	0.16	0.00	0.0%	66.9
7:00	0.19	0.19	0.00	0.0%	67.5
8:00	0.23	0.23	0.00	0.0%	71.0
9:00	0.22	0.22	0.00	0.0%	76.4
10:00	0.21	0.21	0.00	0.0%	81.6
11:00	0.29	0.29	0.00	0.0%	86.0
12:00	0.51	0.51	0.00	0.0%	89.4
13:00	0.87	0.87	0.00	0.0%	92.0
14:00	1.26	0.25	1.01	80.4%	93.6
15:00	1.65	0.31	1.34	81.3%	94.7
16:00	1.99	0.37	1.62	81.5%	95.2
17:00	2.20	0.40	1.80	81.9%	94.6
18:00	2.26	0.54	1.71	75.9%	92.8
19:00	2.16	2.60	-0.43	-20.0%	90.0
20:00	1.92	2.11	-0.19	-10.0%	86.3
21:00	1.66	1.66	0.00	0.0%	82.2
22:00	1.45	1.45	0.00	0.0%	79.5
23:00	1.12	1.12	0.00	0.0%	77.2
0:00	0.78	0.78	0.00	0.0%	75.2
	Reference Energy Use w/o DR (kWh)	Predicted Energy Use w/ DR (kWh)	Change in Energy Use (kWh)	% Daily Load Change	Cooling Degree Hours (Base
Daily	21.75	14.89	-6.86	-31.6%	97.9

Figure 2-7:
Hourly Load Impacts for the Average Residential SDP Customer on a Typical Event Day
1-in-10 Year Weather

TABLE 1: Menu options

Type of Results	Average Customer
Local Capacity Area	All Customers
Day type	Typical Event Day
Weather Year	1-in-10

TABLE 2: Event Day Information

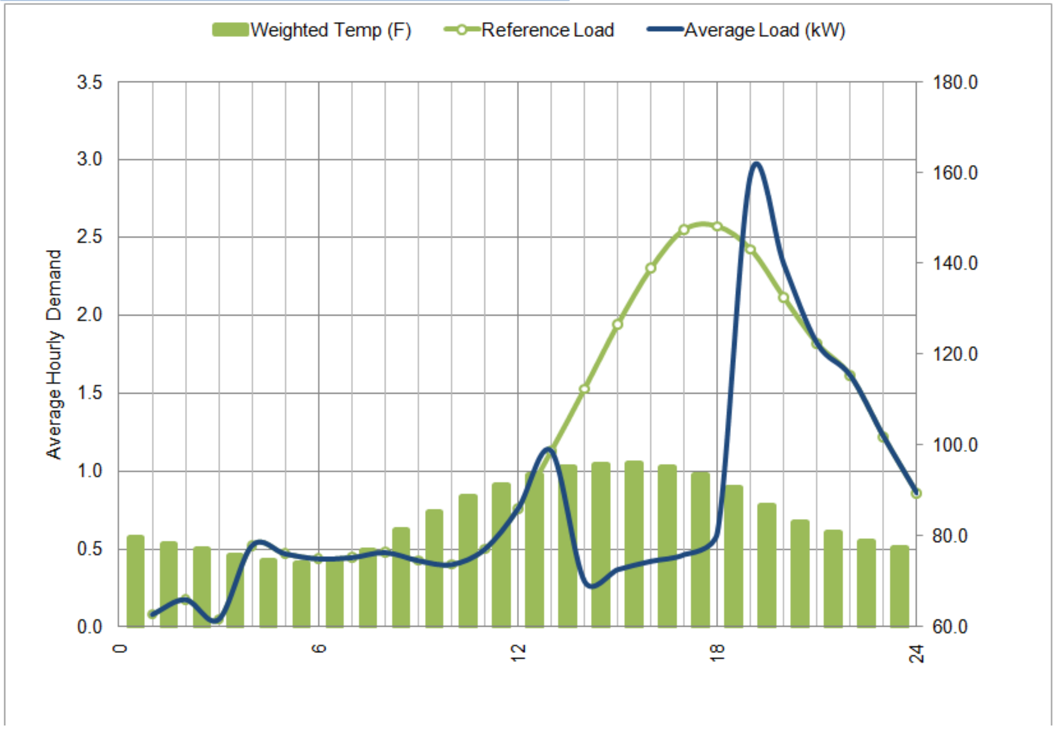
Event Start	1:00 PM
Event End	6:00 PM
TOTAL ENROLLED ACCOUNTS	343,566
Avg. Load Reduction for Event Window	1.74
% Load Reduction for Event Window	80

TABLE 3: Event Participant Characteristics by Region

Local Capacity Region	% of units	Avg Connected Load
LA Basin	76	4.36
Outside LA Basin	10	4.36
Ventura	14	4.36

TABLE 4: Distribution of Participants by Region and Cycling Strategy

Local Capacity Region	Cycling Strategy (% of units)			
	50%	67%	100%	TOTAL
LA Basin	1.7	5.6	68.7	76.0
Outside LA Basin	0.2	0.5	9.1	9.8
Ventura	0.3	0.9	12.9	14.2
TOTAL	2.2	7.1	90.7	100.0



Hour Ending	Average Load w/o DR (kW)	Average Load (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)
1:00	0.08	0.08	0.00	0.0%	79.8
2:00	0.18	0.18	0.00	0.0%	78.3
3:00	0.05	0.05	0.00	0.0%	77.0
4:00	0.52	0.52	0.00	0.0%	75.7
5:00	0.47	0.47	0.00	0.0%	74.7
6:00	0.44	0.44	0.00	0.0%	74.0
7:00	0.44	0.44	0.00	0.0%	74.3
8:00	0.48	0.48	0.00	0.0%	76.8
9:00	0.43	0.43	0.00	0.0%	81.3
10:00	0.40	0.40	0.00	0.0%	85.2
11:00	0.50	0.50	0.00	0.0%	88.6
12:00	0.76	0.76	0.00	0.0%	91.3
13:00	1.13	1.13	0.00	0.0%	93.5
14:00	1.53	0.29	1.23	80.8%	95.2
15:00	1.94	0.37	1.57	81.0%	95.8
16:00	2.30	0.42	1.88	81.6%	96.0
17:00	2.55	0.46	2.08	81.7%	95.2
18:00	2.57	0.61	1.96	76.3%	93.4
19:00	2.42	2.90	-0.48	-20.0%	90.8
20:00	2.11	2.32	-0.21	-10.0%	86.7
21:00	1.82	1.82	0.00	0.0%	83.1
22:00	1.61	1.61	0.00	0.0%	80.9
23:00	1.22	1.22	0.00	0.0%	78.8
0:00	0.86	0.86	0.00	0.0%	77.4
	Reference Energy Use w/o DR (kWh)	Predicted Energy Use w/ DR (kWh)	Change in Energy Use (kWh)	% Daily Load Change	Cooling Degree Hours (Base
Daily	26.78	18.75	-8.03	-30.0%	107.2

Tables 2-5 summarizes per customer load impacts by LCA. The average impact for a typical event day is significantly higher based on 1-in-10 versus 1-in-2 year weather conditions. Customers in the LA Basin tend to provide the highest average load impacts, but not by a very large margin.

Table 2-6 summarizes aggregate load impacts by year, based on enrollment forecasts provided by SCE. Enrollment is expected to steadily increase after 2011. The highest aggregate load impact for 2011 is 568 MW for 1-in-10 year weather conditions in July. The comparable estimate based on 1-in-2 year weather, 507 MW, is 11% less than the 1-in-10 year value. Aggregate load impacts vary by about 20% across months during the summer, from a low of 437 MW in June under 1-in-2 year weather conditions to a high of 507 MW in July. Using 1-in-10 year weather, the monthly aggregate impacts vary from 478 MW in June to 568 MW in July.

These aggregate results are similar to those from 2009. Differences arise for two reasons. First, the ex ante event period in the 2009 report was 1 PM to 6 PM, while here it is 2 PM to 6 PM. This reduces average impacts over the events because impacts during the hour 1 PM to 2 PM are lower than those later in the day. Second, forecasted enrollment for 2011 is lower in this year's report than in the 2009 report.

Table 2-5:
Average Impact per Hour for Event Period (1 to 6 PM) for SDP Residential Program Forecast Year 2011 (kW)

Weather Year	Day Type	LA Basin	Outside LA Basin	Ventura	Total Service Territory
1-in-2	Typical Event Day	1.6	1.4	1.0	1.5
	June Peak	1.5	1.2	1.0	1.4
	July Peak	1.8	1.6	1.2	1.7
	August Peak	1.6	1.5	1.1	1.5
	September Peak	1.7	1.4	1.0	1.6
1-in-10	Typical Event Day	1.8	1.8	1.5	1.7
	June Peak	1.6	1.3	1.4	1.6
	July Peak	1.9	1.9	1.6	1.9
	August Peak	1.8	1.9	1.6	1.8
	September Peak	1.8	1.7	1.5	1.8

Table 2-6:
Aggregate Impact per Hour for Event Period (1 to 6 PM) for SDP Residential Program
Forecast Year 2011

Weather Year	Day Type	2011	2012	2013	2014	2015-2021
1-in-2	Typical Event Day	457	491	535	579	583
	January Peak	0	0	0	0	0
	February Peak	0	0	0	0	0
	March Peak	0	0	0	0	0
	April Peak	69	70	76	82	85
	May Peak	152	158	172	186	190
	June Peak	437	462	503	545	552
	July Peak	507	545	594	643	647
	August Peak	456	499	544	588	588
	September Peak	474	519	565	607	607
	October Peak	261	286	311	332	332
	November Peak	117	128	139	148	148
	December Peak	0	0	0	0	0
1-in-10	Typical Event Day	532	572	623	674	679
	January Peak	0	0	0	0	0
	February Peak	139	136	149	162	168
	March Peak	189	189	206	223	231
	April Peak	171	174	190	206	212
	May Peak	312	323	352	382	389
	June Peak	478	505	550	596	604
	July Peak	568	610	665	720	725
	August Peak	527	577	629	680	680
	September Peak	530	581	632	679	679
	October Peak	313	342	373	398	398
	November Peak	234	256	278	295	295
	December Peak	0	0	0	0	0

Table 2-7 summarizes the average hourly SDP Residential load impacts across the 1 to 6 PM event period by day type under both 1-in-2 and 1-in-10 weather conditions. The impacts vary substantially by hour, month and weather year. Generally speaking, the hour from 4 to 5 PM is the peak hour. On a typical event day under 1-in-2 year weather conditions, the SDP residential program could deliver 548 MW of load relief during the peak hour. On a typical event day under 1-in-10 year conditions, the peak hour load impact is estimated to equal 634 MW. On an hour-by-hour basis, these results are very similar to those reported in the 2009 report, with the only differences being due to lower predicted enrollment for 2011. For example in 2009, the peak hourly predicted load impact was 719 MW during the hour of 4 to 5 PM on a July peak day in a 1-in-10 year. Here the peak hourly predicted load impact is 715 MW during the same hour under the same conditions.

Table 2-7:
Aggregate Impact by Day Type and Hour for SDP Residential Program (MW)
Forecast Year 2011

Weather Year	Day Type	1-2 PM	2-3 PM	3-4 PM	4-5 PM	5-6 PM
1-in-2	Typical Event Day	309	409	494	548	522
	January Peak	0	0	0	0	0
	February Peak	0	0	0	0	0
	March Peak	0	0	0	0	0
	April Peak	13	43	71	99	116
	May Peak	75	123	161	194	209
	June Peak	351	420	467	500	449
	July Peak	413	480	551	569	521
	August Peak	350	445	491	518	474
	September Peak	387	445	514	541	482
	October Peak	276	275	275	257	223
	November Peak	110	135	140	120	81
	December Peak	0	0	0	0	0
1-in-10	Typical Event Day	376	478	572	634	597
	January Peak	0	0	0	0	0
	February Peak	145	152	156	133	110
	March Peak	186	196	203	194	167
	April Peak	104	144	181	210	219
	May Peak	195	278	329	373	385
	June Peak	376	449	513	553	501
	July Peak	462	552	618	633	574
	August Peak	420	509	569	591	545
	September Peak	436	516	590	602	508
	October Peak	335	337	329	305	259
	November Peak	262	267	250	216	173
	December Peak	0	0	0	0	0

3 Commercial Summer Discount Plan

The commercial SDP program is similar to the residential SDP program. Events are called for both groups at the same time. Commercial customers receive a credit on their summer season electric bills and, in return, SCE has the option to cycle the customer's central AC compressor. Customers served under the following tariffs are eligible for the commercial SDP program: GS-1, TOU-GS-1, GS-2, TOU-GS-3 and TOU-8.

There are two SDP plans offered to commercial customers – the Base plan and the Enhanced plan.

- The Base SDP Plan allows SCE to turn off the central AC a maximum of 15 times (up to 6 hours per time, multiple times per day if necessary) during the summer season; and
- The Enhanced SDP Plan allows SCE to turn off the AC for an unlimited number of days (up to 6 hours per time) during the summer season.

The Enhanced Plan currently provides twice the credit as the Base Plan. Within each plan, the bill credit is proportional to the number of AC tons enrolled in the program and increases with the cycling percentage. Both plans offer three cycling options: 30% (AC disconnected for 9 minutes out of every 30 minutes), 50% (AC disconnected for 15 minutes out of every 30 minutes) and 100% (AC disconnected continuously during the cycling event).

In exchange for allowing SCE to control their units, participants receive a bill credit during the entire summer season. For customers on a GS-1 or TOU-GS-1 rate, the incentive payment ranges from a low of $0.014/ton of AC per day for the Base Plan and a 30% cycling strategy to a high of $0.40/ton for the 100% cycling strategy for the Enhanced Plan. For customers on a GS-2, TOU-GS-3, or TOU-8 rate, the monthly incentive payment ranges from a low of $0.42/ton of AC for the Base Plan and a 30% cycling strategy to a high of $12.00/ton for the 100% cycling strategy for the Enhanced Plan. Over the course of the four-month summer season (from June 1st to October 1st), the incentives would range from a low of roughly $8 to a high of almost $240 for a customer with a 5-ton AC unit.

During the summer of 2010, SCE conducted two system-wide events: a 30-minute event on July 29th and a 2-3 hour event (depending on customer rate) on September 27th.

Ex ante load impact estimates have been produced for each year for 2011 through 2021. Enrollment forecasts were provided by SCE. Estimates are provided for each of the three LCAs in SCE's service territory and for all customers combined. The ex ante impacts reflect the load reduction capability of the program under a standard set of 1-in-2 and 1-in-10 year weather conditions.

3.1 Participant Population Characteristics

As of February 2010, nearly 10,000 commercial accounts were enrolled in the program.[2] In comparison to residential participants, commercial participants generally have more AC units. Table 3-1 summarizes the distribution of SDP participants, characterized by account, number of devices and tons of AC, by

[2] An effort is being made to obtain a more up-to-date Summer Discount Plan population file before the filing of the final draft of this report. In any case, the population has changed little in the past year.

customer size and cycling strategy chosen. On average, large accounts (200 kW and up) have approximately 35 AC units per account while medium and small commercial participants have roughly 7 and 2 units per account, respectively. Large customers constitute 4.2% of commercial participants and 32.6% of the overall AC tonnage. Overall, 65.3% of the devices are on the 100% cycling strategy, 24.3% are on the 50% cycling strategy, 9.4% are on the 30% cycling plan and the remainder 0.5% are on 40% cycling.

Table 3-1:
SDP Commercial Participants, Devices, and Air Conditioning Tonnage By Customer Size and Cycling Option

Size Category	Unit	Cycling Option				
		30%	40%	50%	100%	Total
Large C&I (>200kW)	Participants	37	2	148	219	406
	Devices	864	65	5,709	7,718	14,356
	Tons	3,204	254	29,181	45,576	78,215
Medium C&I (20-200kW)	Participants	386	20	935	2,715	4,056
	Devices	2,348	100	8,825	18,250	29,523
	Tons	9,439	298	38,118	82,838	130,694
Small C&I (<20kW)	Participants	490	22	1,279	3,412	5,203
	Devices	951	31	2,270	6,393	9,645
	Tons	2,956	111	7,276	20,520	30,863
Total	Participants	913	44	2,362	6,346	9,665
	Devices	4,163	196	16,804	32,361	53,524
	Tons	15,600	663	74,575	148,934	239,771

Table 3-2 provides additional detail about the participant, device and AC tonnage distribution by business type and cycling strategy as of the beginning of summer 2010. The majority of participants and tonnage are concentrated among schools, religious organizations and offices. The concentration across business types is important because different businesses have different operating hours and seasonal patterns that affect the load impacts customers can provide.

Although schools represent only 10.7% of participant accounts, they constitute 49.7% of the AC units and 50.2% of the tonnage because they tend to be large. The second most significant industry group is comprised of religious organizations. They account for 19.9% of enrolled tonnage. Both schools and religious organizations have a majority of enrolled tonnage on 100% cycling.

Table 3-2:
SDP Participants, Devices and Air Conditioner Size by Customers Size and Business Type, Summer 2010

Industry	Unit	Cycling Selection				
		30	40	50	100	Total
Manufacturing	Participants	45	2	142	332	521
	Devices	158	13	1,093	1,016	2,280
	Tons	734	8	3,569	4,655	8,966
Wholesale	Participants	55	4	218	323	600
	Devices	173	5	949	698	1,825
	Tons	901	22	4,747	2,876	8,546
Retail stores	Participants	209	9	317	1,376	1,911
	Devices	1,207	16	620	2,280	4,123
	Tons	3,827	54	2,699	11,044	17,624
Offices and Services	Participants	382	21	866	1,977	3,246
	Devices	995	90	2,242	4,989	8,316
	Tons	3,864	306	8,927	18,406	31,504
Schools	Participants	47	4	414	568	1,033
	Devices	1,127	60	10,403	15,037	26,627
	Tons	3,419	234	47,582	69,099	120,334
Religious Organizations	Participants	102	2	306	1,473	1,883
	Devices	322	2	1,223	7,591	9,138
	Tons	1,756	6	5,979	40,010	47,751
Other or unknown	Participants	73	2	99	297	471
	Devices	181	10	274	750	1,215
	Tons	1,100	33	1,071	2,842	5,046
All	Participants	913	44	2,362	6,346	9,665
	Devices	4,163	196	16,804	32,361	53,524
	Tons	15,600	663	74,575	148,934	239,771

3.2 Analysis Methodology

In order to estimate commercial reference loads and load impacts, SCE commissioned the installation of AC loggers on a sample of commercial SDP customers. AC loggers were installed on an initial sample of 398 commercial customers. Of these, data was retrieved from 392 loggers with usable data,[3] providing a sample 98% as large as the initial target. SCE has decided to leave the loggers in the field on the same set of customers to measure AC loads during the summer of 2011. Two summers of data in a row on the same set of customers will be very useful for understanding and predicting commercial AC loads.

[3] The six loggers lost were due to broken loggers returned at the end of the summer.

Table 3-3 shows the distributions of total AC tonnage in the logger sample and the commercial population across LCAs and cycling options. The sample matches the population quite well. Population weights were applied to the data based on tonnage in each LCA and cycling option, which should ameliorate the small differences that do exist. The weighted AC logger data was used to estimate the impact of the September event and to forecast impacts for future events.

During installation of the AC loggers, the technician checked the control devices to make sure they had the ability to receive a signal and turn off the AC compressor. 96% of units passed this test, which means that communication failure probably does not lead to a large reduction in load impact among this population.

Table 3-3:
Distributions of AC Tonnage in the SDP Commercial Population and Logger Sample (Percentages shown)

Cycling Option	LA Basin		Outside LA Basin		Ventura		Total	
	Population	Sample	Population	Sample	Population	Sample	Population	Sample
30	6	7	0	0	1	1	7	8
50	28	22	1	1	3	3	31	25
100	43	36	4	1	14	30	62	67
Total	77	65	5	2	18	34	100	100

During the summer of 2010, SCE conducted two system-wide events: a 30-minute event on July 29th and a 2-3 hour event (depending on customer rate) on September 27th. In addition to the system wide events, district 79 experienced 4 events, but the number of AC logger sample customers in district 79 was insufficient for modeling the impacts of these events.

Regression analysis of AC logger data from the sample described above was used to estimate ex post impacts for the 2-3 hour system-wide event during the summer of 2010.[4]

Ex ante reference load estimates were calculated based on the same model used to estimate ex post reference loads. For this purpose, the existence of AC logger data was very useful. It allowed for reference load estimates that accurately represent load in the SDP commercial population. This is in contrast to previous years, where proxies were used to estimate reference loads. For this reason, this year's estimates should be more reliable than previous years'.

However, because there was only one system-wide event, the lack of variation in temperature during event hours was insufficient to calculate future event impacts over the full range of ex ante conditions. Therefore ex ante predictions of future impacts were estimated by incorporating our findings of average percent load reductions from San Diego Gas and Electric Company's load research sample for the Summer Saver program. These percent load reductions were then applied to reference load predictions to estimate event impacts.

[4] The 30-minute system-wide event was also modeled, but results are not reported. These can be included in the final draft if necessary.

3.2.1 Regression Model Development, Specifications and Parameters

Individual customer regressions were used to model customer AC usage during the summer of 2010. All commercial customers were subject to the same model designed to capture both weather sensitive and non-weather sensitive load. Several validity tests were performed and are also discussed.

The regression model used to predict reference loads was developed to predict AC load given the time of day, day of week and recent temperature conditions. The model includes:

- Weighted averages of cooling degree hours over time, to capture how AC load depends on temperature above a specific threshold;
- Variables reflecting customer operating schedules, including month-of-year and time-of-day characteristics;
- Interactions between weighted averages of cooling-degree hours and scheduling variables; and
- Event variables that capture the effects of SDP events.

The specific variables in the model are described in Table 3-4. The regression specification was:

$$kWh = a + \sum_{i=1}^{24} b_i * hour_i + \sum_{i=1}^{24}\sum_{j=7}^{9} c_{ij} * (WACDH * hour_i * month_j) + \sum_{i=1}^{22} d_i * event_i + e$$

Table 3-4:
Description of SDP Commercial Regression Variables

Variable	Description
a	a is an estimated constant
b-d	b-d are estimated parameters
WACDH	A weighted average of the past 24 hours of cooling degree hours (defined as the maximum of 0 or temperature – 65°F), which is correlated with AC load
$hour_i$	Dummy variables representing the hours of the day, designed to estimate the effect of operating schedule on kWh
$month_j$	Dummy variables for month of the year, designed to pick up seasonal effects in operating schedules
$event_j$	Dummy variable representing each potential event, designed to pick up the event effect
e	The error term

There was only one, full-length event during the summer of 2010, which does not provide enough information to make predictions over a range of future conditions. Therefore, ex ante event impacts were imputed using results from SDG&E's load research sample. The 2010 SDP commercial load data was used to predict the reference load for the ex ante weather days and the resulting impacts were calculated applying the appropriate percent impact from Table 3-5. As was the case for the residential part of the analysis, event impacts have been calculated for the 2010 Summer Saver program as well, but the 2009 events took place over a more relevant range of weather conditions.

Table 3-5:
Percent Load Reductions by Cycling Strategy and Temperature Bin[5]

Temperature (°F)	Cycling Option			
	30	40*	50	100*
<80	18	21	26	52
80-85	21	24	28	56
85-90	22	26	33	65
90+	22	27	34	67

*Predicted using 30 and 50% cycling data

3.2.2 Model Accuracy and Validity Assessment

We employ several validity tests on our results, including out-of-sample and in-sample testing. These tests will help to verify that the model accurately estimates load under event-like conditions (hot, weekday and afternoon hours). In-sample tests establish that the model is explaining the variation in AC load during the summer of 2010. Out-of-sample tests demonstrate that the model accurately predicts load on days not included in the regression analysis. Out-of-sample tests guard against over-fitting, which may lead to a model that performs well in-sample but fails to accurately predict load out-of-sample.

In-sample Testing

For the model to be useful, it 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 data the model was fit to. 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 the regressions 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.

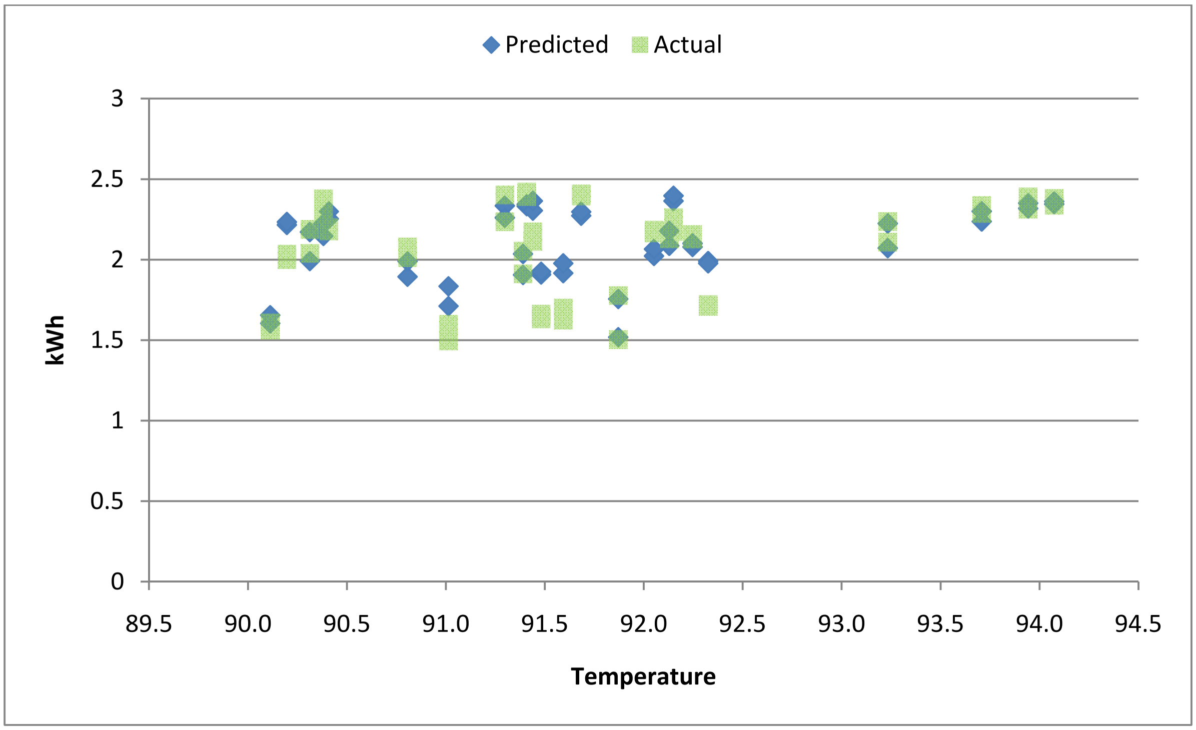
The average R-squared value of the individual regressions is 58%. The R-squared for aggregate load over every half-hour of the summer is 98%. An individual customer's usage is difficult to predict because it depends on many unobservable factors. Aggregate loads are easier to predict, because the unobservable factors are randomly distributed across time and customers. This means that they tend to

[5] Based on 2009 SDG&E Summer Saver Commercial Load Research Sample. The 40% cycling values are interpolated from the 30% and 50% data, as SDG&E did not have a 40% cycling option in its program. SDG&E does not have a 100% commercial cycling option. The percent load reductions were estimated by reducing doubling the 50% cycling impact estimates.

cancel out with aggregation. SDP events are likely to be called at times of very high temperature, therefore the model must accurately fit load at high temperatures in particular.

Figure 3-1 shows actual and observed loads for non-event hours during the summer of 2010 when the temperature exceeds 90°F. This figure demonstrates the accuracy of model predictions during non-event days. There is little systematic difference between the predicted and actual loads in Figure 3-1. On average, predicted loads exceed observed loads by less than 3%.

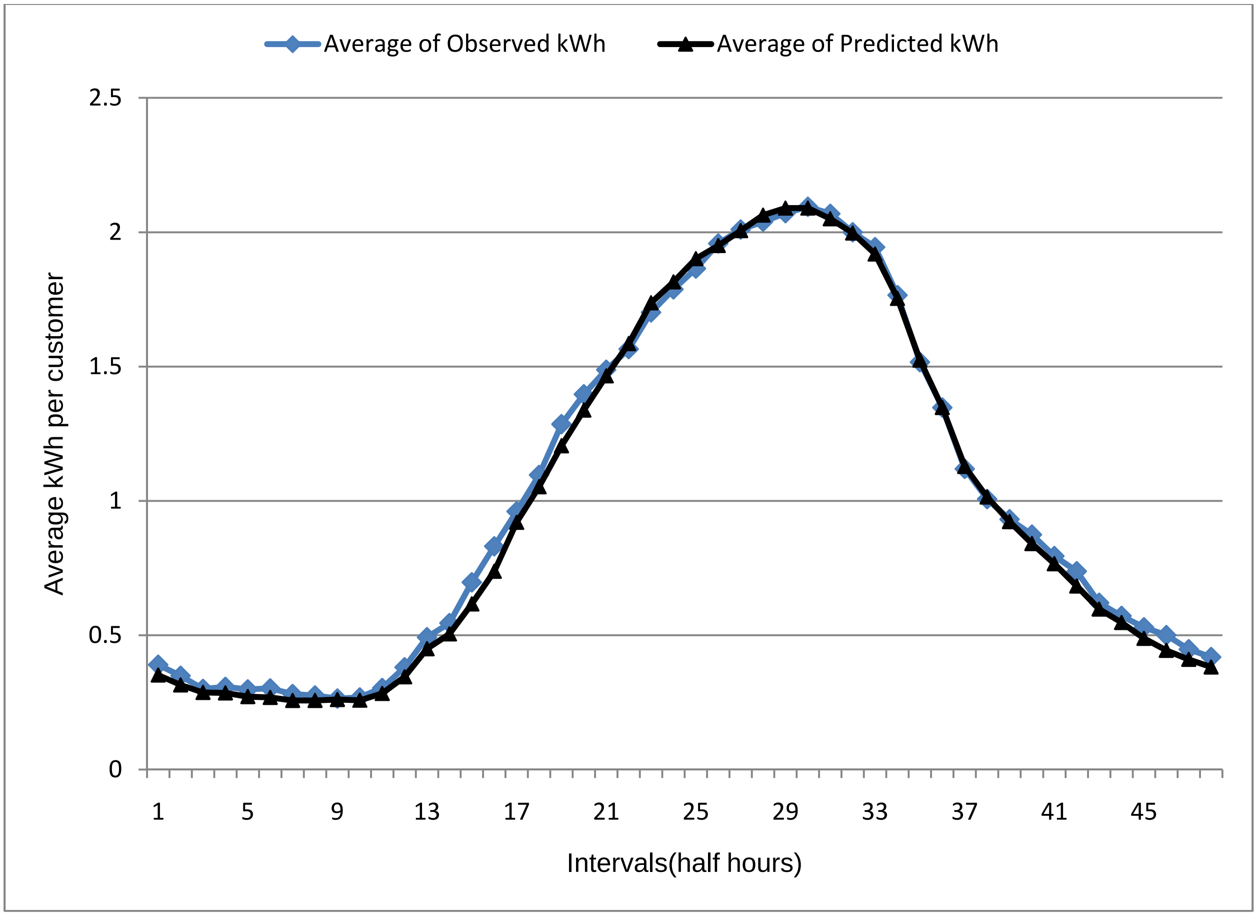
Figure 3-1:
Actual and Predicted Average Commercial Load for 1 PM to 8 PM, Non-Event Days When the Temperature Exceeds 90°F



Out-of-sample Testing

Out-of-sample testing consists of withholding random summer days from the regression analysis, and then checking to see how well the model predicts usage on those days. In other words, out-of-sample testing checks the model's accuracy for days that are not used in the fitting of the model, but for which the actual load is known. The three out-of-sample days were randomly selected from the 20 hottest summer non-event days. Figure 3-2 compares average predicted load to actual load for the three out-of-sample days.

Figure 3-2:
Actual and Predicted Average Load for Out-of-sample Days



3.3 Ex Post Load Impact Estimates

On September 27th, 2010 SCE held a system wide event from 3:16 PM to 6:13 PM (the event ended for customers on the ASP rate 45 minutes earlier). There was also a half-hour event on July 29th from 7:00 PM to 7:30 PM. Event impacts for each event were estimated using the regression model described above.

September 27th was the hottest day of the summer, with large reference loads and impacts. The average temperature during the event was 101°F, with temperatures averaging 104°F during the three hours immediately before the event. The average reference load per AC unit during the event was 1.9 kW, and the average load impact per AC unit was 0.9 kW, or 47% of reference load. Event impacts were decreased somewhat by the fact that the event took place later in the day, which means that some commercial establishments may have closed and turned off their AC before the end of the event.

The estimated impact of 47% of reference load was determined using only 2010 SDP logger data. The ex ante methodology of borrowing impacts from Summer Saver was not used for the ex post estimation. However, had that method of impact estimation been used, the estimated impact would have been 50%

of reference load. That these two values match so closely provides corroboration that the Summer Saver impacts used for ex ante estimation below a good proxy for SDP impacts.

On July 29th the event impact was 0.1 kW for the half-hour event. The impact is much lower due both to substantially lower temperatures (73°F at the time of the event) and to the fact that the event came later in the day.

3.4 Ex Ante Load Impact Estimates

Figures 3-3 and 3-4 show the estimated reference load and load reduction for an average AC unit for the typical event day based on 1-in-2 and 1-in-10 year weather conditions for the forecast year 2011. The load impacts vary substantially by hour due to variation in the underlying AC load.

In a 1-in-2 weather year on a typical event day, the estimated load impact per AC unit declines from 0.9 kW at 4 PM to 0.6 kW at 6 PM. Across the 1 to 6 PM event window, the average commercial participant AC unit provides an average load reduction of 0.8 kW on a typical event day.

The load impacts under 1-in-10 year weather conditions follow a similar pattern, but are higher due to higher AC loads and higher duty cycles. For the typical event day, the average AC unit load impact over the same event window is 1.0 kW, or 20% higher than the 1-in-2 weather year. In aggregate, the SDP commercial program is forecasted to produce an average aggregate hourly load reduction of roughly 55 MW on the highest system load day based on 1-in-10 year weather conditions.

Figure 3-3:
Ex Ante Estimates for the Average Commercial AC Unit on a Typical Event Day with1-in-2 Year Weather

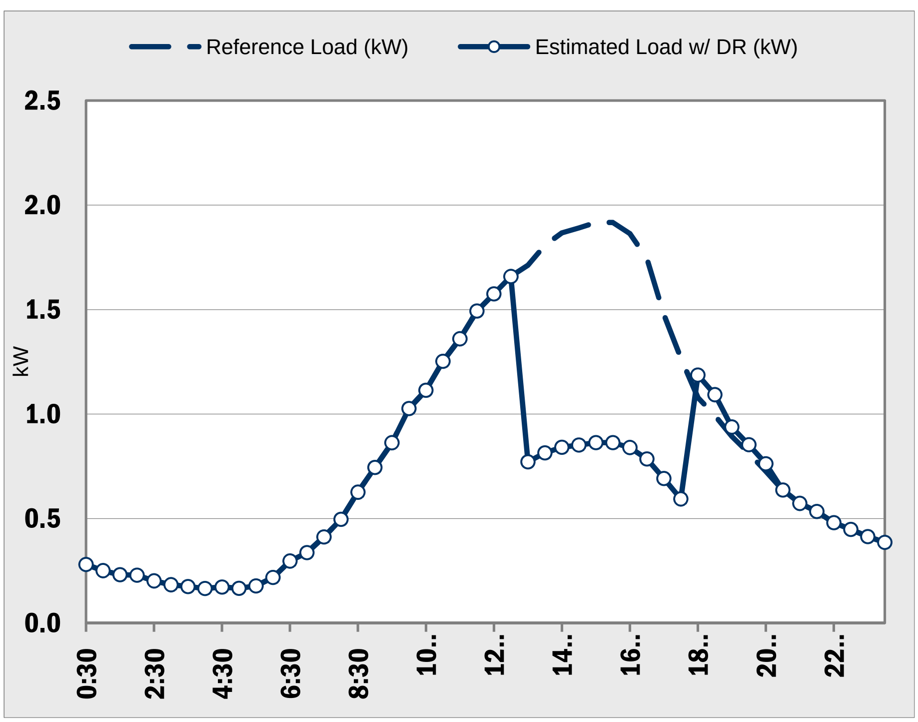
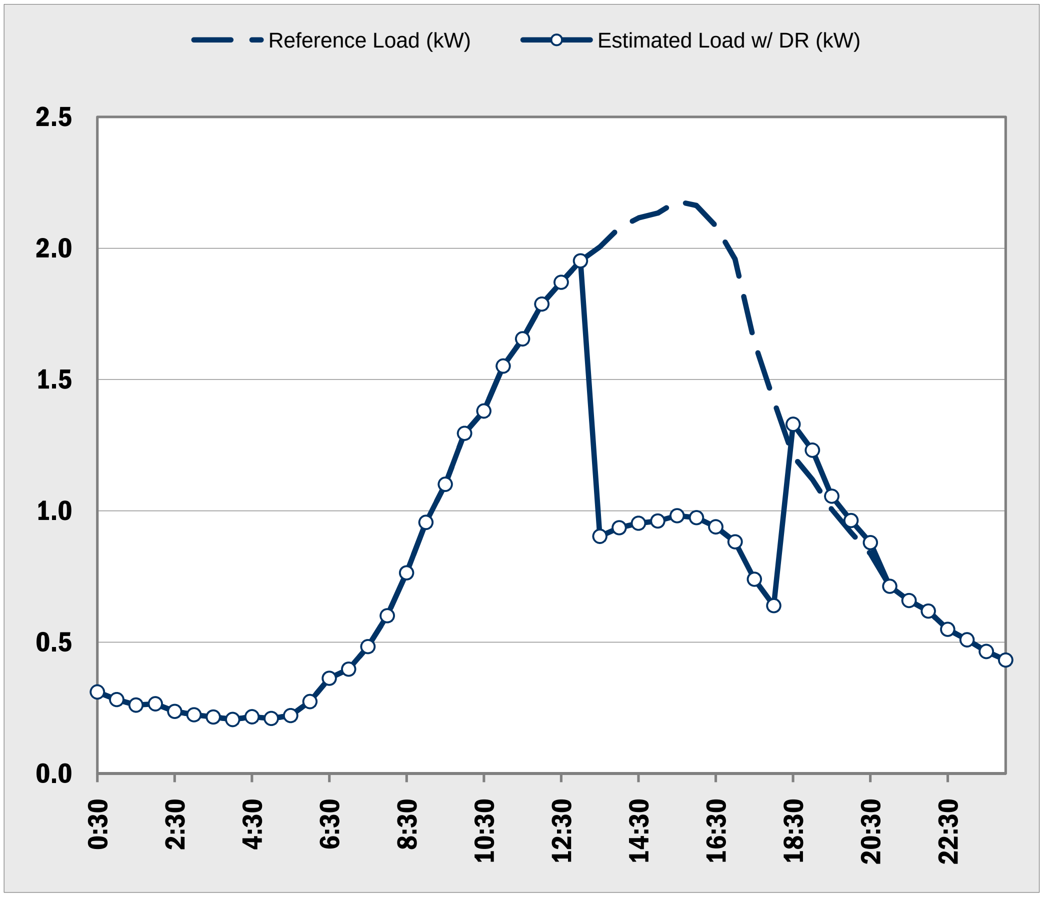


Figure 3-4:
Ex Ante Estimates for the Average Commercial AC-Unit on a Typical Event Day with 1-in-10 Year Weather



Tables 3-6 summarizes per AC unit by LCA. The average impact for a typical event day is about 20% higher based on 1-in-10 versus 1-in-2 year weather conditions. Customers in the Outside LA Basin LCA tend to provide the highest average load impacts.

Tables 3-7 summarizes aggregate load impact by year, based on enrollment forecasts provided by SCE. Enrollment in the program is expected to grow steadily over the next five years. The highest aggregate load impact for 2011 is 63 MW for 1-in-10 year weather conditions in August. The comparable estimate based on 1-in-2 year weather, 56 MW, is 11% less than the 1-in-10 year value. Aggregate load impacts vary substantially across months, from a low of 30 MW in June under 1-in-2 year weather conditions to a high of 56 MW in August. Using 1-in-10 year weather, the monthly aggregate impacts vary from 33 MW in June to 63 MW in August.

These aggregate results are about 30% lower than those reported in the 2009 report. This is not due to any change in the program or the SDP population. The 2009 estimates were based on a model of whole-building interval data for only large commercial customers. Results were then scaled down based on AC tonnage to assign impacts to medium and small commercial customers. That method was reasonable, given the data available. The 2010 results, however, should be viewed as much more reliable because they are based on actual measured AC load for a representative sample of the commercial SDP population.

Table 3-6:
Average Impact for 1-6 PM for Commercial Customers Forecast Year 2011 (kW)

Weather Year	Day Type	LA Basin	Ventura	Outside LA Basin	Total Service Territory
1-in-2	Typical Event Day	0.8	0.9	1.2	0.8
	June Peak	0.4	0.6	0.9	0.5
	July Peak	0.6	0.6	1.1	0.7
	August Peak	0.9	0.9	1.2	0.9
	September Peak	0.7	0.9	1.0	0.8
1-in-10	Typical Event Day	0.9	1.0	1.3	1.0
	June Peak	0.4	0.7	1.0	0.6
	July Peak	0.8	0.6	1.1	0.8
	August Peak	1.0	1.0	1.3	1.0
	September Peak	0.8	1.0	1.0	0.8

Table 3-7:
Average Aggregate SDP Commercial Program Impacts
1 PM to 6 PM Forecast Years 2011-2021 (MW)

Weather Year	Day Type	2011	2012	2013	2014	2015-2021
1-in-2	Typical Event Day	51	55	60	64	64
	June Peak	30	33	35	38	38
	July Peak	42	46	49	53	53
	August Peak	56	61	66	71	71
	September Peak	49	53	58	61	61
1-in-10	Typical Event Day	59	64	69	74	74
	June Peak	33	36	39	42	43
	July Peak	47	51	55	59	60
	August Peak	63	69	74	80	80
	September Peak	52	56	61	65	65

Table 3-8 summarizes the average hourly SDP commercial load resources across the 1 to 6 PM event period by day type under both 1-in-2 and 1-in-10 weather conditions. The impacts vary substantially by hour, month and weather year. For the August system peak day under 1-in-10 weather year conditions, the program is capable of delivering an average of 63 MW of load reduction over the course of an event. However, the load impacts vary substantially by hour. For the 1-in-10 system peak day the load impact for the hour ending at 6 PM is 31% lower than for the hour ending at 4 PM.

Table 3-8:
Aggregate Impact by Day Type and Hour (MW)
1-in-2 and 1-in-10 Weather Conditions

Weather Year	Day Type	1:00-2:00 PM	2:00-3:00 PM	3:00-4:00 PM	4:00-5:00 PM	5:00-6:00 PM
1-in-2	Typical Event Day	51	55	58	52	39
	June Peak	28	33	34	31	24
	July Peak	41	44	46	43	34
	August Peak	57	61	62	58	44
	September Peak	49	53	55	52	37
1-in-10	Typical Event Day	62	65	66	59	44
	June Peak	31	37	38	34	26
	July Peak	47	50	51	49	38
	August Peak	65	69	70	65	48
	September Peak	54	57	58	51	39

3.5 Recommendations for the Summer Discount Program

FSC makes two recommendations the SDP program. First, we recommend SCE utilize smart meter data for future analysis of the residential SDP program. Second, we recommend that SCE call test events for the sake of analysis.

We recommend that SCE make use of the increasing available smart meter data for analysis of the residential program. In 2009, SDG&E collected data on whole building load and directly metered AC load, enabling the direct comparison of load impacts using the two types of data.[6] The impacts were analyzed using the same regression method and almost identical models in order to assess the effectiveness of the evaluation with whole building rather than end-use data. The impact estimates from both the whole building and end-use data were nearly identical. Since then, FSC has corroborated this approach by comparing impacts calculated from AC logger data with impacts calculated from smart meter data at SDG&E again and for two other utilities. In each case, smart meter data has produced quite accurate impact measurements.

[6] Stephen George, Josh Bode, Josh Schellenberg and Seth Morgan. *2009 Load Impact Evaluation of San Diego Gas & Electric Company's Summer Saver Program.* April 1, 2010.

However, because commercial hourly load data is more idiosyncratic, and there are fewer smart meters in the commercial population, we believe it was a valuable decision to leave AC loggers on the 2010 commercial sample in order to collect data for 2011.

We recognize that SCE is limited in its ability to call multiple test events and to direct them at specific, representative groups of customers. We do recommend though, that SCE continue to call at least one test event per summer.

4 Agricultural and Pumping Interruptible Program

The Agricultural and Pumping Interruptible (AP-I) program provides a monthly credit to eligible agricultural and pumping customers for allowing SCE to temporarily interrupt electric service to their pumping equipment during CAISO or other system emergencies. As of September 30, 2010, there were 802 customers enrolled in the AP-I program.

In 2010, an AP-I event was called for the first time since November 2008. There were two AP-I events in total. The first event was on July 29th and lasted from 6:57 PM to 7:28 PM. The second 2010 event was on September 27th from 3:16 PM to 4:31 PM. Ex post load impact estimates for these events are presented in this section along with an assessment of switch failure based on an analysis of load data. Ex ante load impact estimates are provided in Section 4.5.

4.1 AP-I Program Background and History

Agricultural and pumping customers with a measured demand of 37 kW or greater, or with at least 50 horsepower of connected load per service account, are eligible to participate in the AP-I program. Participating customers must already be served under an agricultural and pumping rate schedule. The AP-I program is not available to customers receiving the off-peak credit provided under Schedule PA-1 or to customers served under experimental rate schedules. The AP-I program may also not be available in certain areas of SCE's territory where communication signaling equipment has not been installed or signal strength is inadequate to activate or deactivate an interruption. With some restrictions, AP-I participants may enroll in other programs, but cannot be paid for the same reduced load.

When an interruption is deemed necessary and is allowed under the terms of the tariff, SCE sends a signal to the load control device installed on a customer's pumping equipment. The signal automatically turns off the equipment for the entire duration of the interruption event. AP-I customers can request to receive courtesy notifications of the start and end time of an interruption through means of email, pager and/or text message to a cell phone. The number of interruptions cannot exceed one per day, 4 in any calendar week and 25 per calendar year. The duration of an interruption cannot exceed 6 hours per interruption, 40 hours per calendar month or 150 hours per calendar year.

In exchange for allowing SCE to interrupt pumping service during times of emergencies, AP-I customers receive a monthly credit. The credits vary between customers on a TOU rate and those on a non-TOU rate. For the roughly 95% of participants on a TOU rate, the credit is based on their directly measured average hourly peak and mid-peak demand. Customers receive $17.22 per summer average on-peak kW, $3.66 per summer average mid-peak kW and $1.25 per winter average mid-peak kW. For the remaining 5% of customers on a non-TOU rate, the credit is $0.01164/kWh, which applies to energy use all year long. Prior to 2009, the incentive consisted solely of a flat kWh credit for all participants.

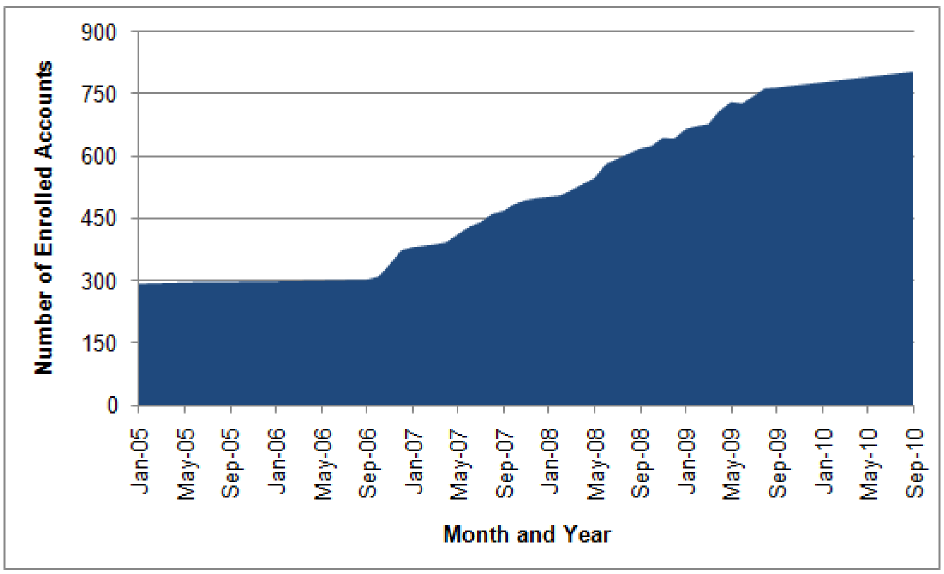
The AP-I program has been in operation since the 1970s, although it was closed to new enrollment starting in 1998. As a result of the increased need for DR resources after the energy crisis in 2000-2001, the program was reopened on April 3, 2001.[7] In March 2006, SCE was authorized to increase marketing

[7] Pursuant to D.01-04-006.

of the AP-I program with the objective of significantly increasing enrollment. As part of this effort, SCE eliminated the up-front charge to customers for AP-I equipment and installation. Considerable effort was made to increase enrollment since SCE had not actively marketed the AP-I program for a number of years and customer awareness was low.

As a result of the increased marketing and outreach, the number of enrolled service accounts increased from roughly 300 at the beginning of 2006 to 664 service accounts by the end of January 2009, and to 802 by the end of September 2010. The impact of this marketing can be seen in Figure 4-1. Enrollment has more than doubled since March 2006 when the marketing of AP-I was approved. Enrollment is highest in the Ventura LCA, where 533 customers are enrolled. The second largest region in terms of enrollment is the LA Basin LCA, with 198 enrollees, followed by the Outside LA Basin LCA, with 71 participants.

Figure 4-1:
Number of Enrolled Accounts
January 2005 to September 2010



AP-I is expected to experience continued enrollment growth over the next few years. In August 2012, AP-I enrollment is expected to equal 928 participants and 990 in August 2014. Afterwards, enrollment is assumed to remain constant until the end of the ex ante forecast period (2021).[8]

4.2 AP-I Analysis Methodology

When an AP-I event is called, the direct load control device completely shuts down the electricity supply to the pump. For most pumps the load drop is nearly instantaneous, although some systems are configured to ramp down pumps over the period of approximately five minutes. In most instances, the

8 Stephen George and Josh Bode. "Enrollment Projections and Load Impacts for SCE's Demand Response and Dynamic Pricing Programs." February 23, 2011. (Prepared by FSC for SCE in conjunction with its 2012-2014 DR Application)

pump is directly metered, but this is not true in every case. A relatively small number of customers have additional loads such as lighting on the same circuit as the pumps. Those loads, however, are a minor fraction of the overall measured loads, particularly since pumps are at a minimum 50 hp (approximately 35 kW).

Because the measured load is almost exclusively pumps, when the direct load control switch is activated, the expected load impact is approximately equal to the reference load. The aggregate load impact across all accounts should equal the aggregate reference load minus the load associated with any accounts that have non-working switches. Given this, the primary focus of the analysis was on estimating reference loads. An estimate of working switches was also developed based on the 2010 events.

4.2.1 AP-I Model Development

The regression model used to predict the reference load was designed to accurately predict average load for the agricultural pumps in the AP-I program given the time of day, day of week and month. The focus was primarily on the accuracy of the predictions in the months and hours of the day when an event is likely to be called.

Functional form was closely considered, and then several specifications were tested using the ordinary least squares regression technique with robust standard error corrections. The selection of the final regression model was based on its accuracy under normal and extreme conditions and its theoretical consistency. The final model has energy use for agricultural pumping driven by variables that capture the following factors:

- Typical load shapes associated with operational schedules;
- Pricing variables that capture the impacts of the variable cost of electricity that AP-I customers typically face;
- Temperature and rainfall variables designed to capture the impact of weather on agricultural pumping; and
- DR event variables to capture load impacts associated with AP-I events and other DR program events for customers that are dually-enrolled.

Individual regressions were run for the 817 customers with sufficient data available for analysis. The same specification was used for all customers. The dependent variable was the average hourly energy use for each AP-I agricultural pump and the explanatory variables are summarized in Table 4-1.

Mathematically, the regressions can be expressed by:

$$kW_t = A + \sum_{i=1}^{24}\sum_{j=1}^{12} B_{ij} \times Hour_i \times Month_j + + \sum_{i=1}^{24}\sum_{j=1}^{5} C_{ij} \times Hour_i \times DayType_j$$

$$+ \sum_{i=1}^{24} D_i + Hour_i + PriceRatio_t + \sum_{i=1}^{24} E_i \times Hour_i \times TotalCDH_t$$

$$+\sum_{i=1}^{24} F_i \times Hour_i \times TotalCDHsqr_t + \sum_{i=1}^{24} G_i \times Hour_i \times TotalHDH_t$$
$$+\sum_{i=1}^{24} H_i \times Hour_i \times TotalHDHsqr_t + \sum_{i=1}^{24} I_i \times Hour_i \times WeeklyRain_t$$
$$+\sum_{i=1}^{24} J_i \times Hour_i \times WeeklyCDD_t + \sum_{i=1}^{24} K_i \times Hour_i \times OtherDR_t$$
$$+\sum_{i=1}^{24}\sum_{j=1}^{3} L_{ij} \times Hour_i \times Eventday_j + \varepsilon_t$$

Table 4-1:
AP-I Model Variables and Definitions

Variable	Definition
kW_t	Average hourly demand (kW) for each time period
A	Estimated constant term
B_{ij} through L_{ij}	Regression model parameters
$Hour_i$	Series of binary variables for each hour, which account for the basic hourly load shape of the customer after other factors such as weather and prices are accounted for
$DayType_j$	Series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday)
$PriceRatio_t$	Ratio of the current cost of energy to the average daily cost of energy per kwh
$Month_j$	Series of binary variables for each month designed to reflect seasonality in loads
$TotalCDH_t$	Sum of cooling degree hours (base 65) for the day
$TotalCDHsqr_t$	$TotalCDH_t$ squared
$TotalHDH_t$	Sum of heating degree hours (base 65) for the day
$TotalHDHsqr_t$	$TotalHDH_t$ squared
$WeeklyRain_t$	Weighted average measure of cumulative rainfall from the trailing seven days, with the weighting for the trailing two days equivalent to that of the previous five days
$WeeklyCDD_t$	Weighted average measure of cooling degree days from the trailing seven days, with the weighting for the trailing two days equivalent to that of the previous five days
$OtherDR_t$	Binary variable representing a customer's participation in another DR event
$Eventday_t$	Binary variable representing an AP-I event day[9]
e_t	Is the error term

[9] There were 3 AP-I events called during the period from 2008 through 2010.

4.2.2 AP-I Model Accuracy and Validity Assessment

Although regressions were run for each individual customer in the AP-I program, what matters most is that the reference loads for all customers combined, or for selected groups of customers, are accurate. Given that load impacts are equal to the reference load (after a small adjustment for switch failure), any error in the estimated reference load would cause an error in the estimated load impact.

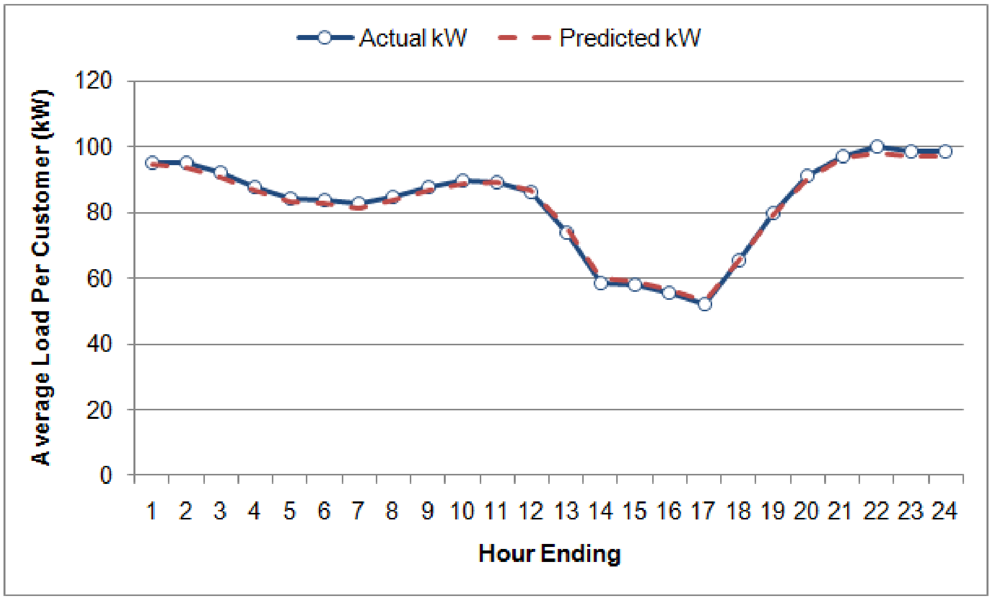
Out-of-sample Validation

Considering that AP-I events are usually called on high system load days during the summer, it is important that the model predicts accurately at high temperatures. In the first test of model accuracy, a series of out-of-sample validations is conducted. Rather than running the model on all of the available load data, a group of five randomly selected high temperature weekdays is withheld from the estimation. Although these five days are not included in the estimating sample, the model is used to predict load on those days. This process is repeated three times so that out-of-sample predictions of load are generated for the top 15 maximum temperature weekdays for each customer.

This validation process most closely aligns with what is expected of the model in the ex post and ex ante analyses. In the ex ante analysis, the model is used to simulate the reference load and load with DR under 1-in-2 and 1-in-10 weather year scenarios. The ex post analysis estimates load reductions by predicting load if the event was not called. In both of these analyses, out-of-sample predictions are generated for scenarios in which actual, unperturbed load data is not available. Therefore, out-of-sample validation using randomly selected high temperature weekdays is a logical test to determine which model is most accurate.

Figure 4-2 shows the results of the out-of-sample validation for the top 15 maximum temperature weekdays for each customer. As seen in the figure, the model accurately predicts load on high temperature weekdays even if those days are not included in the estimating sample. The difference between actual and predicted load did not exceed 2.5% in any hour. More importantly, the percentage error is low during the afternoon when events are most likely to be called. Between 1 PM and 6 PM, the model slightly over predicts by 1.7%.

Figure 4-2:
Actual v. Predicted Average Load
Out-of-Sample Validation for Top 15 Maximum Temperature Weekdays

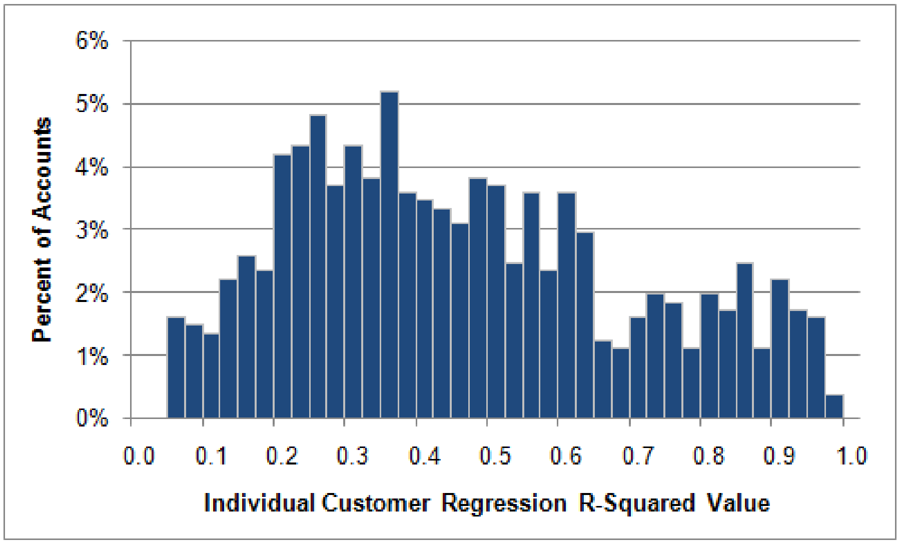


Goodness of Fit Measures

Although the regressions were estimated at the individual customer level, from a policy standpoint, the focus is less on how the regressions perform for individual customers than it is on how the regressions perform for the average participant and for specific customer segments. Overall, individual customers exhibited more variation and less consistent energy use patterns than the aggregate participant population. Likewise, the regressions are better at explaining the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. Put differently, it is more difficult to fully explain how a customer from a specific industry behaves on an hourly basis than it is to explain how the average customer in that industry behaves on an hourly basis. Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions for specific customer segments and for the average customer overall.

Figure 4-3 shows the distribution of R-squared values from the individual customer regressions for AP-I customers. Roughly half of the individual customer regressions had R-squared values above 0.45, which suggests that the model predicts relatively well for most AP-I customers. The lower one-third of all individual regressions had R-squared statistics up to 0.3.

Figure 4-3:
Distribution of R-squared Values from Individual Regressions for AP-I Customers



In order to estimate the average customer R-squared values for each crop type, LCA or the program as a whole, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:[10]

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

Table 4-2:
Description of the R-squared Variables

Variable	Description
y_t	actual energy use at time t
$\hat{y}_t$	regression predicted energy use at time t
$\bar{y}$	average energy use across all time periods

[10] Technically, the R-squared value needs to be adjusted based on the number of parameters and observations from each regression. Given that the number of observations per regression was typically over 8,000, the effects of the adjustment were anticipated to be minimal. As a result, the unadjusted R-squared is presented in order to avoid the complication of tracking the number of observations and parameters from each individual regression.

Table 4-3 summarizes the amount of variation explained by the regression model by crop type and LCA. For all customers, the model has an aggregate R-squared value of 0.93, which means that the model explains 93% of variation in aggregate AP-I load. The lowest R-squared value is among customers in the other crop-type segment, which has the least amount of customers. Among segments with a sizeable number of customers, the aggregate R-squared value is 0.89 or higher, which suggests that the model predicts accurately across the most important segments. Although many of the individual regression R-squared values are low (as shown in Figure 4-3), the model is accurate when predicting aggregate AP-I load overall and across key segments of the population.

Table 4-3:
Aggregate R-squared Values by Crop Type and LCA

Group Type	Segment	Number of Customers	Aggregate R-Squared
Crop Type	Dairy, Beef & Poultry Farms	257	0.95
	Other	35	0.76
	Vegetable, Fruit & Grain Farms	287	0.91
	Water Supply Systems & Recreation	238	0.91
LCA	LA Basin	209	0.89
	Outside LA Basin	75	0.91
	Ventura	533	0.93
	Overall	**817**	**0.93**

4.3 AP-I Ex Post Load Impact Estimates

Ex post load impact estimates based on hourly interval data for the two AP-I events in 2010 are provided in this section. In 2010, there were no time periods when AP-I was in effect for a complete hour interval. Although AP-I was activated for slightly over an hour on September 27th, the event time period was spread across the interval ending at 4 PM and the interval ending at 5 PM. For AP-I, we focus on the final hour interval in which each event was in effect (7 PM to 8 PM on July 29th and 4 PM to 5 PM on September 27th). Although these events officially ended at 7:28 PM and 4:31 PM, each has an effect for the remainder of the hour because there is a time lag between the end of each event and when AP-I customers manually reactivate their pumps. Nonetheless, these ex post load impact estimates may be slightly conservative because an event was not in effect for the entire hour interval in which each event ended.

On September 27, 2010, Southern California experienced a short, but intense heat wave that almost resulted in a new all-time system peak for SCE. Between 4 PM and 5 PM on September 27th, SCE system load nearly reached 23,000 MW, which had only happened once before in 2007 when system load peaked at 23,130 MW. At 3:16 PM on that day, AP-I was activated and the event lasted until 4:31 PM for the 802 participants that were enrolled at the time.

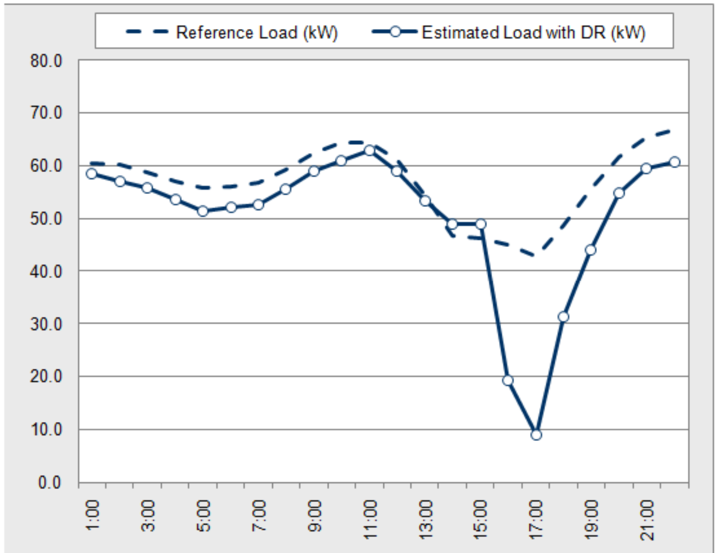
Figure 4-4 shows the average load impact per AP-I customer in each hour on September 27th. From 4 PM to 5 PM (the 2010 system peak hour), the load drop was 33.8 kW per participant. Figure 4-5 shows the aggregate load impact for each hour of the day. The aggregate load drop from 4 PM to 5 PM was 27.1 MW. This represents a 78.8% reduction relative to the reference load of 34.4 MW. From 5 PM to 6 PM, the aggregate load impact was still 14.1 MW as many AP-I customers did not manually reactivate their pumps immediately after the event. These ex post results show that AP-I delivered substantial load impacts when they were needed most during on the 2010 system peak day.

In each figure, it is apparent that the model over predicts during the beginning of the day on September 27th. From midnight to 11 AM, the reference load is 5.8% above the estimated load with DR on average. For AP-I, activations are expected to have little effect in the hours leading up to the event because load impacts are driven by the direct load control technology. Although the model over predicts during the beginning of the day, the reference load and estimated load with DR are similar in the hours immediately preceding the event. From 11 AM to 3 PM, there is less than a 1% difference between the reference load and estimated load with DR. Therefore, it is expected that the model predicts accurately during event hours even though it seems to over predict load during the beginning of the day.

Figure 4-4:
Average AP-I Ex Post Load Impact (kW) per Participant for September 27, 2010

TABLE 1: Menu options

Type of Result	Average Enrolled Account
Customer Type	ALL
Event Date	27-Sep-10
Event Start	3:16:00 PM
Event End	4:31:00 PM
Enrolled Accounts	802



[1] Due to size of the time interval, the figure does not reflect the semi-instantaneous drop in load attributable to the direct load control technology employed

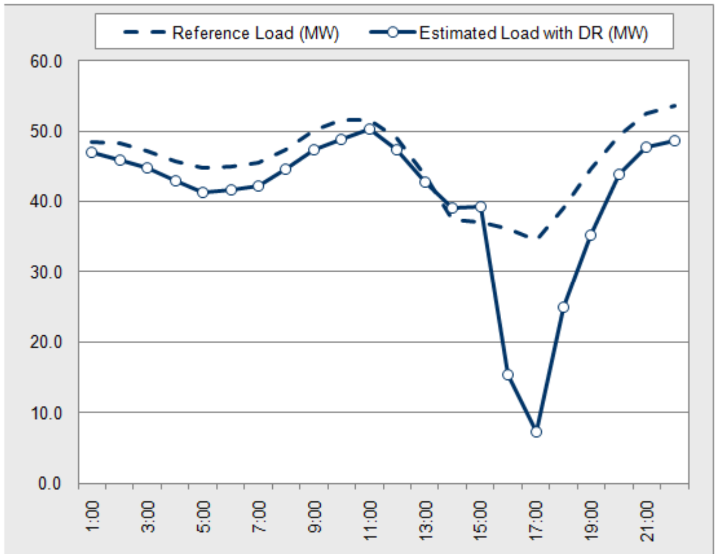
Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	60.4	58.5	1.9	3.2%	73.5	0.6	1.4	1.9	2.5	3.3
2:00	60.2	57.1	3.1	5.1%	72.6	1.7	2.5	3.1	3.6	4.4
3:00	58.7	55.8	2.9	4.9%	71.1	1.5	2.3	2.9	3.4	4.2
4:00	56.9	53.5	3.4	6.0%	70.5	2.1	2.9	3.4	4.0	4.8
5:00	55.8	51.5	4.4	7.8%	68.5	3.0	3.8	4.4	4.9	5.7
6:00	56.0	52.0	4.0	7.1%	68.2	2.6	3.4	4.0	4.5	5.3
7:00	56.8	52.6	4.2	7.4%	67.6	2.8	3.6	4.2	4.7	5.5
8:00	59.1	55.6	3.5	5.9%	69.0	2.2	2.9	3.5	4.0	4.8
9:00	62.4	59.0	3.4	5.4%	74.0	2.0	2.8	3.4	3.9	4.7
10:00	64.3	60.9	3.4	5.3%	80.5	2.1	2.9	3.4	4.0	4.7
11:00	64.4	62.8	1.6	2.5%	86.0	0.3	1.0	1.6	2.1	2.9
12:00	61.2	59.1	2.1	3.5%	90.7	0.8	1.6	2.1	2.7	3.5
13:00	54.4	53.2	1.2	2.1%	94.4	-0.2	0.6	1.2	1.7	2.5
14:00	46.7	48.8	-2.1	-4.5%	96.4	-3.4	-2.6	-2.1	-1.5	-0.8
15:00	46.2	48.9	-2.7	-5.9%	97.8	-4.0	-3.3	-2.7	-2.2	-1.4
16:00	45.1	19.2	25.9	57.5%	98.9	24.6	25.4	25.9	26.5	27.3
17:00	42.9	9.1	33.8	78.8%	99.1	32.5	33.3	33.8	34.4	35.2
18:00	48.7	31.2	17.6	36.1%	98.1	16.2	17.0	17.6	18.1	18.9
19:00	55.5	44.0	11.6	20.8%	94.8	10.2	11.0	11.6	12.1	12.9
20:00	61.6	54.8	6.8	11.1%	89.8	5.5	6.3	6.8	7.4	8.2
21:00	65.4	59.4	6.0	9.2%	86.1	4.7	5.5	6.0	6.6	7.4
22:00	66.8	60.6	6.2	9.3%	82.8	4.9	5.6	6.2	6.7	7.5
23:00	67.4	61.5	5.9	8.8%	79.3	4.6	5.4	5.9	6.5	7.3
0:00	67.4	62.3	5.2	7.6%	78.0	3.8	4.6	5.2	5.7	6.5

	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	1,384.4	1,231.3	153.1	0.1	400.5	n/a	n/a	n/a	n/a	n/a

Figure 4-5:
Aggregate AP-I Ex Post Load Impact (MW) for September 27, 2010

TABLE 1: Menu options

Type of Result	Aggregate
Customer Type	ALL
Event Date	27-Sep-10
Event Start	3:16:00 PM
Event End	4:31:00 PM
Enrolled Accounts	802



[1] Due to size of the time interval, the figure does not reflect the semi-instantaneous drop in load attributable to the direct load control technology employed

Hour Ending	Reference Load (MW)	Estimated Load with DR (MW)	Load Impact (MW)	%Load Reduction	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	48.4	46.9	1.5	3.2%	73.5	0.5	1.1	1.5	2.0	2.6
2:00	48.3	45.8	2.5	5.1%	72.6	1.4	2.0	2.5	2.9	3.5
3:00	47.1	44.8	2.3	4.9%	71.1	1.2	1.9	2.3	2.7	3.4
4:00	45.7	42.9	2.7	6.0%	70.5	1.7	2.3	2.7	3.2	3.8
5:00	44.8	41.3	3.5	7.8%	68.5	2.4	3.1	3.5	3.9	4.6
6:00	44.9	41.7	3.2	7.1%	68.2	2.1	2.7	3.2	3.6	4.3
7:00	45.6	42.2	3.4	7.4%	67.6	2.3	2.9	3.4	3.8	4.4
8:00	47.4	44.6	2.8	5.9%	69.0	1.7	2.4	2.8	3.2	3.9
9:00	50.0	47.3	2.7	5.4%	74.0	1.6	2.3	2.7	3.1	3.8
10:00	51.6	48.8	2.7	5.3%	80.5	1.7	2.3	2.7	3.2	3.8
11:00	51.6	50.4	1.3	2.5%	86.0	0.2	0.8	1.3	1.7	2.4
12:00	49.1	47.4	1.7	3.5%	90.7	0.6	1.3	1.7	2.1	2.8
13:00	43.6	42.7	0.9	2.1%	94.4	-0.2	0.5	0.9	1.4	2.0
14:00	37.5	39.1	-1.7	-4.5%	96.4	-2.8	-2.1	-1.7	-1.2	-0.6
15:00	37.1	39.2	-2.2	-5.9%	97.8	-3.2	-2.6	-2.2	-1.7	-1.1
16:00	36.2	15.4	20.8	57.5%	98.9	19.7	20.3	20.8	21.2	21.9
17:00	34.4	7.3	27.1	78.8%	99.1	26.1	26.7	27.1	27.6	28.2
18:00	39.1	25.0	14.1	36.1%	98.1	13.0	13.7	14.1	14.5	15.2
19:00	44.5	35.3	9.3	20.8%	94.8	8.2	8.8	9.3	9.7	10.3
20:00	49.4	43.9	5.5	11.1%	89.8	4.4	5.0	5.5	5.9	6.6
21:00	52.5	47.6	4.8	9.2%	86.1	3.8	4.4	4.8	5.3	5.9
22:00	53.6	48.6	5.0	9.3%	82.8	3.9	4.5	5.0	5.4	6.0
23:00	54.1	49.3	4.7	8.8%	79.3	3.7	4.3	4.7	5.2	5.8
0:00	54.1	49.9	4.1	7.6%	78.0	3.1	3.7	4.1	4.6	5.2

	Reference Energy Use (MWh)	Energy Use with DR (MWh)	Change in Energy Use (MWh)	% Daily Load Change	Cooling Degree Hours (Base 65)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	1,110.3	987.5	122.8	0.1	400.5	n/a	n/a	n/a	n/a	n/a

Figure 4-6 shows the aggregate reference load and estimated load with DR for the other AP-I event in 2010, which occurred on July 29th. This day had a short event that lasted from 6:57 PM to 7:28 PM for 784 AP-I customers. From 7 PM to 8 PM, the load drop was 50.7 kW per participant and 39.7 MW on aggregate. From 8 PM to 9 PM, the aggregate load impact was still nearly 20 MW as many AP-I customers did not manually reactivate their pumps immediately after the event. Relative to the reference load of 52.8 MW, the load reduction was 75.3%. Although the percent load impact was similar to the September 27th event, the aggregate load reduction was 12.6 MW higher because usage for AP-I customers is substantially higher later in the day. Considering that AP-I customers are highly responsive to TOU price signals, the load impacts are sensitive to the hours in which an event is called.

Figure 4-6:
Aggregate Reference Load and Estimated Load with DR for the July 29, 2010 AP-I Event

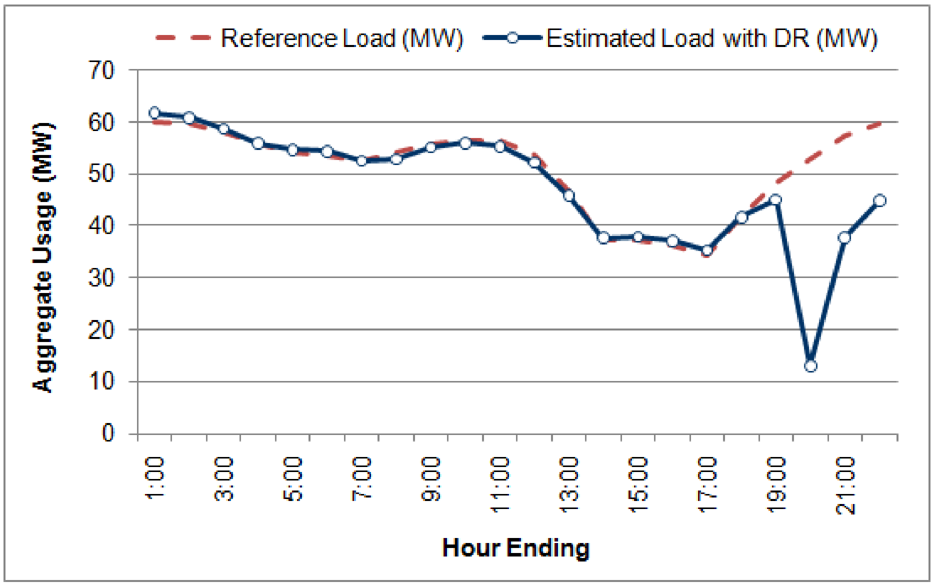


Table 4-4 shows the 2010 average and aggregate AP-I ex post load impact estimates by event date and LCA. The percent load reductions were consistent among the LCAs with the most participants. In the LA Basin LCA, the percent load reduction was 70.1% on July 29th and 73.0% on September 27th. In the Ventura LCA, AP-I customers consistently provided around 80% load impacts. Aggregate load reductions were concentrated in the Ventura LCA, which accounted for 69% for the July 29th event and 81% for the September 27th event.

Table 4-4:
2010 Average and Aggregate AP-I Ex Post Load Impact Estimates by Event Date and LCA

Event Date and Hour	LCA	Number of Customers	Avg. Reference Load (kW)	Avg. Load with DR (kW)	Avg. Load Reduction (kW)	% Load Reduction	Aggregate Load Reduction (MW)
July 29th, 7-8 PM	LA Basin	199	69.6	20.8	48.8	70.1%	9.7
	Outside LA Basin	73	56.9	20.4	36.4	64.1%	2.7
	Ventura	512	67.9	14.4	53.5	78.8%	27.4
	All Customers	**784**	**67.3**	**16.7**	**50.7**	**75.3%**	**39.7**
Sept. 27th, 4-5 PM	LA Basin	198	31.7	8.5	23.1	73.0%	4.6
	Outside LA Basin	71	21.5	9.4	12.1	56.2%	0.9
	Ventura	533	50.3	9.2	41.1	81.6%	21.9
	All Customers	**802**	**42.9**	**9.1**	**33.8**	**78.8%**	**27.1**

4.4 AP-I Switch Failure Analysis

When devices are successfully activated, load impacts for the AP-I program are essentially equivalent to the reference load. However, not all pumps are shut down when events are called, due to either equipment or communication failures. The 2010 event data were used to estimate the percent of customers for whom communication with the load control switch was successful.

To begin the analysis, FSC calculated each customer's maximum load and compared it with the value in the hour prior to each event. If the ratio of electricity use in that hour on the event day to the maximum load was less than 0.05, the customer was deemed to not be operating their pump and was dropped from the sample. After this screening analysis, there were 433 observations left for the July 29th event and 342 from the September 27th event. Although there were more participants in the September event, the number of observations for this analysis is lower because AP-I customers operate their pumps less frequently towards the end of the summer.

For the remaining customers, load in the hour prior to the event was compared with load in the final hour of the event period (July 29th, 7 to 8 PM and September 27th, 4 to 5 PM). There was a wide distribution of load reductions across participants. This leaves a significant number of participants that appeared to drop only a portion of their load. A break point was utilized in an effort to separate normal fluctuation of load from event participation. The distribution of load drop percentages was examined carefully and a 50% load drop was set as the breakpoint. A drop of less than 50% between the hour prior to the event and the final hour of the event period was determined to be unperturbed fluctuation in load. Load drops of greater than 50% were deemed to be consistent with successful switch communication.

Table 4-5 provides the estimated switch success rates by event date. For the two 2010 events overall, the switch success rate was 82.8%. The results of the November 7, 2008 event come from last year's AP-I evaluation and are included to show how the estimated switch success rate has changed over time.

From the 2008 event to the September 2010 event, the estimated switch success rate increased from 78% to 85.4%. After each event, SCE is able to determine which switches may not be functioning properly and can visit the customer site to repair them. This may explain why the switch success rate increased substantially from July 29th to September 27th. On the other hand, the number of customers with their pump in operation before each event is different, which suggests that there may be a difference in the mix of customers. Without more event data, it is difficult to conclusively determine whether or not the switch success rate is improving substantially.

Table 4-5: Estimated AP-I Switch Success Rates by Event Date

Event Date	Number of Observations	Switch Success Rate
Nov. 7, 2008	311	78.0%
July 29, 2010	433	80.8%
Sept. 27, 2010	342	85.4%
Overall (2010)	**775**	**82.8%**

As indicated in last year's AP-I evaluation, SCE plans to significantly increase switch success rates during the 2012 to 2014 time period. As such, the ex ante analysis assumes that switch success rates improve over time. Table 4-6 provides the forecast of AP-I switch success rates that is used in the ex ante analysis. For 2011, the overall 2010 switch success rates for each LCA are used. As shown in the table, the Outside LA Basin LCA starts out with a relatively low rate of 67% because it had a higher rate of switch failure in 2010. Starting with the next funding cycle in 2012, the switch success rates for each LCA improve to 95% by August 2014 and they are held constant for all forecast years afterwards.

Table 4-6: Forecast of AP-I Switch Success Rates Used in Ex Ante Analysis

Forecast Year	LA Basin	Outside LA Basin	Ventura	Overall
2011	79%	67%	86%	83%
2012 (August)	83%	74%	88%	86%
2013 (August)	89%	85%	92%	90%
2014 (August)	95%	95%	95%	95%
2015-2021	95%	95%	95%	95%

4.5 AP-I Ex Ante Load Impact Estimates

The AP-I program grew from 664 to 802 accounts from January 2009 to September 2010. The program is expected to experience continued enrollment growth over the next few years. In August 2012, AP-I enrollment is expected to equal 928 participants and 990 in August 2014. Afterwards, enrollment is assumed to remain constant until the end of the ex ante forecast period (2021).[11] For ex ante purposes, the load impacts of new participants are assumed to be the same as existing AP-I customers.

Figures 4-7 and 4-8 show the reference load and estimated load with DR for the average customer on a typical event day based on 1-in-2 and 1-in-10 year weather conditions for the year 2014. Impacts are reported for 2014 because it is the year in which enrollment growth and switch success rates reach a steady state. For a 1-in-2 typical event day, the estimated load impact for the average participant is 48.9 kW from 1 PM to 6 PM. The average impact estimate is slightly higher for the typical event day in a 1-in-10 weather year. As a result of the improved switch success rates, the load impact is 95% of the reference load under both weather year conditions.

The remainder of the hourly ex ante load impact estimates that are required by the protocols for AP-I, including uncertainty adjusted estimates, can be found in the electronic appendix titled, "SCE 2010 AP-I Ex Ante Load Impact Tables."

[11] Stephen George and Josh Bode. "Enrollment Projections and Load Impacts for SCE's Demand Response and Dynamic Pricing Programs." February 23, 2011. (Prepared by FSC for SCE in conjunction with its 2012-2014 DR Application)

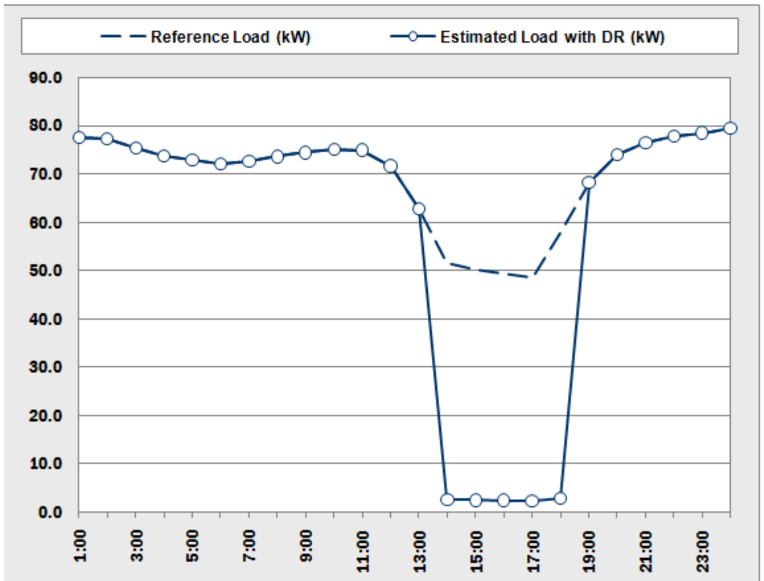
Figure 4-7:
AP-I Average Load Impact (kW) per Customer in 2014
for a Typical Event Day Based on 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average Enrolled Account
Weather Year	1-in-2
Forecast Year	2014
Day Type	Typical Event Day
Customer Characteristic	All Customers
Expected Switch Success Rate (August 2014)	95.0%

TABLE 2: Output

Number of Accounts	990
Switch Success Rate	95.0%
Average Load Impact (kW) (1-6pm)	48.9
% Load Impact (1-6pm)	95.0%



Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	% Load Impact	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
1:00	77.5	77.5	0.0	0.0%	71.4	-2.1	-0.8	0.0	0.8	2.1
2:00	77.2	77.2	0.0	0.0%	69.0	-2.1	-0.9	0.0	0.9	2.1
3:00	75.4	75.4	0.0	0.0%	67.3	-2.1	-0.9	0.0	0.9	2.1
4:00	73.7	73.7	0.0	0.0%	66.2	-2.1	-0.9	0.0	0.9	2.1
5:00	72.9	72.9	0.0	0.0%	64.5	-2.1	-0.9	0.0	0.9	2.1
6:00	72.2	72.2	0.0	0.0%	63.1	-2.1	-0.9	0.0	0.9	2.1
7:00	72.7	72.7	0.0	0.0%	63.1	-2.1	-0.8	0.0	0.8	2.1
8:00	73.6	73.6	0.0	0.0%	67.1	-2.1	-0.9	0.0	0.9	2.1
9:00	74.5	74.5	0.0	0.0%	73.2	-2.1	-0.9	0.0	0.9	2.1
10:00	75.0	75.0	0.0	0.0%	78.1	-2.1	-0.8	0.0	0.8	2.1
11:00	74.9	74.9	0.0	0.0%	82.9	-2.1	-0.9	0.0	0.9	2.1
12:00	71.6	71.6	0.0	0.0%	86.3	-2.1	-0.9	0.0	0.9	2.1
13:00	62.7	62.7	0.0	0.0%	89.3	-2.1	-0.9	0.0	0.9	2.1
14:00	51.4	2.6	48.9	95.0%	91.0	46.8	48.0	48.9	49.7	51.0
15:00	50.1	2.5	47.6	95.0%	92.7	45.5	46.8	47.6	48.5	49.7
16:00	49.3	2.5	46.9	95.0%	93.3	44.8	46.0	46.9	47.7	49.0
17:00	48.5	2.4	46.1	95.0%	93.2	44.0	45.2	46.1	46.9	48.1
18:00	57.8	2.9	54.9	95.0%	92.3	52.9	54.1	54.9	55.8	57.0
19:00	68.2	68.2	0.0	0.0%	90.3	-2.1	-0.9	0.0	0.9	2.1
20:00	74.0	74.0	0.0	0.0%	87.3	-2.1	-0.9	0.0	0.9	2.1
21:00	76.4	76.4	0.0	0.0%	83.3	-2.1	-0.9	0.0	0.9	2.1
22:00	77.9	77.9	0.0	0.0%	80.4	-2.1	-0.9	0.0	0.9	2.1
23:00	78.5	78.5	0.0	0.0%	78.1	-2.1	-0.9	0.0	0.9	2.1
0:00	79.5	79.5	0.0	0.0%	76.1	-2.1	-0.9	0.0	0.9	2.1
	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Change in Energy Use	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
						10th	30th	50th	70th	90th
Daily	1,665.8	1,421.4	244.4	14.7%	249.0	-86.1	109.2	244.4	379.6	574.9

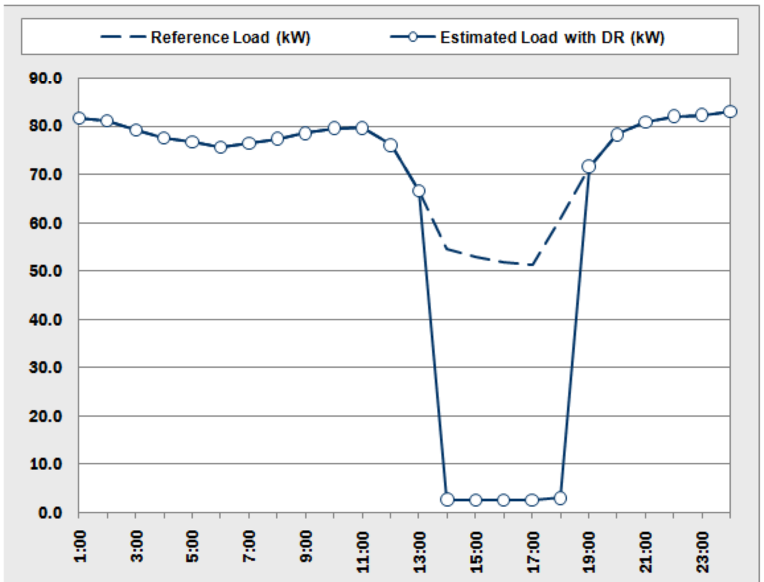
Figure 4-8:
AP-I Average Load Impact (kW) per Customer in 2014
for a Typical Event Day Based on 1-in-10 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average Enrolled Account
Weather Year	1-in-10
Forecast Year	2014
Day Type	Typical Event Day
Customer Characteristic	All Customers
Expected Switch Success Rate (August 2014)	95.0%

TABLE 2: Output

Number of Accounts	990
Switch Success Rate	95.0%
Average Load Impact (kW) (1-6pm)	51.6
% Load Impact (1-6pm)	95.0%



Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	% Load Impact	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	81.7	81.7	0.0	0.0%	79.4	-2.1	-0.9	0.0	0.9	2.1
2:00	81.0	81.0	0.0	0.0%	77.9	-2.1	-0.9	0.0	0.9	2.1
3:00	79.1	79.1	0.0	0.0%	76.3	-2.1	-0.9	0.0	0.9	2.1
4:00	77.5	77.5	0.0	0.0%	74.2	-2.1	-0.9	0.0	0.9	2.1
5:00	76.7	76.7	0.0	0.0%	72.9	-2.1	-0.9	0.0	0.9	2.1
6:00	75.7	75.7	0.0	0.0%	71.6	-2.1	-0.9	0.0	0.9	2.1
7:00	76.4	76.4	0.0	0.0%	71.5	-2.1	-0.9	0.0	0.9	2.1
8:00	77.4	77.4	0.0	0.0%	74.1	-2.1	-0.9	0.0	0.9	2.1
9:00	78.5	78.5	0.0	0.0%	78.5	-2.1	-0.9	0.0	0.9	2.1
10:00	79.6	79.6	0.0	0.0%	82.8	-2.1	-0.9	0.0	0.9	2.1
11:00	79.6	79.6	0.0	0.0%	86.4	-2.1	-0.9	0.0	0.9	2.1
12:00	76.1	76.1	0.0	0.0%	89.6	-2.1	-0.9	0.0	0.9	2.1
13:00	66.6	66.6	0.0	0.0%	92.4	-2.1	-0.9	0.0	0.9	2.1
14:00	54.6	2.7	51.9	95.0%	94.4	49.8	51.0	51.9	52.8	54.0
15:00	53.0	2.6	50.3	95.0%	96.0	48.2	49.5	50.3	51.2	52.4
16:00	51.8	2.6	49.2	95.0%	96.9	47.2	48.4	49.2	50.1	51.3
17:00	51.2	2.6	48.7	95.0%	97.1	46.6	47.8	48.7	49.5	50.7
18:00	60.8	3.0	57.7	95.0%	96.1	55.6	56.9	57.7	58.6	59.8
19:00	71.7	71.7	0.0	0.0%	94.5	-2.1	-0.9	0.0	0.9	2.1
20:00	78.2	78.2	0.0	0.0%	91.2	-2.1	-0.9	0.0	0.9	2.1
21:00	80.8	80.8	0.0	0.0%	86.9	-2.1	-0.9	0.0	0.9	2.1
22:00	82.0	82.0	0.0	0.0%	84.7	-2.1	-0.9	0.0	0.9	2.1
23:00	82.3	82.3	0.0	0.0%	81.9	-2.1	-0.9	0.0	0.9	2.1
0:00	83.0	83.0	0.0	0.0%	79.9	-2.1	-0.9	0.0	0.9	2.1

	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Change in Energy Use	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	1,755.5	1,497.7	257.8	14.7%	347.3	-74.3	121.9	257.8	393.7	589.9

Table 4-7 shows the aggregate on-peak AP-I ex ante load impact estimates for each monthly system peak day by weather year and forecast year. In accordance with the revised resource adequacy hours, the peak period is defined as 1 PM to 6 PM from April through October and 4 PM to 9 PM from November through March. Once enrollment and the switch success reach a steady state in the 2015 to 2021 time period, the program is expected to be capable of delivering up to 58 MW, which occurs during the May monthly peak under 1-in-10 weather conditions. SCE system load typically peaks during August and September. For these monthly peaks in a 1-in-2 and 1-in-10 weather year, aggregate impacts are expected to increase by 25% from 2011 to 2014 as a result of new enrollment and an improved switch success rate.

Table 4-7:
AP-I Aggregate On-Peak Load Impacts (MW)
for Each Monthly System Peak Day by Weather Year and Forecast Year

Weather Year	Month	Peak Period	2011	2012	2013	2014	2015-2021
1-in-2	Jan	4-9 PM	18.3	20.6	22.4	24.3	25.5
	Feb	4-9 PM	19.4	21.7	23.6	25.6	26.6
	Mar	4-9 PM	24.3	27.0	29.4	32.0	33.1
	Apr	1-6 PM	36.6	40.4	43.9	47.7	49.0
	May	1-6 PM	39.1	42.8	46.5	50.4	51.4
	Jun	1-6 PM	38.0	41.3	44.7	48.4	49.0
	Jul	1-6 PM	36.9	39.7	42.9	46.4	46.7
	Aug	1-6 PM	37.2	39.8	43.0	46.6	46.6
	Sep	1-6 PM	35.1	37.7	40.8	43.9	43.9
	Oct	1-6 PM	36.6	39.6	42.9	46.0	46.0
	Nov	4-9 PM	29.5	32.1	34.8	37.1	37.1
	Dec	4-9 PM	20.3	22.1	24.0	25.3	25.3
1-in-10	Jan	4-9 PM	18.4	20.7	22.5	24.4	25.6
	Feb	4-9 PM	21.0	23.5	25.6	27.8	29.0
	Mar	4-9 PM	32.9	36.5	39.8	43.3	44.8
	Apr	1-6 PM	39.3	43.3	47.1	51.1	52.5
	May	1-6 PM	44.2	48.3	52.4	56.9	58.0
	Jun	1-6 PM	41.1	44.6	48.3	52.4	53.1
	Jul	1-6 PM	39.3	42.3	45.7	49.4	49.7
	Aug	1-6 PM	38.8	41.5	44.8	48.5	48.5
	Sep	1-6 PM	39.2	42.1	45.5	49.0	49.0
	Oct	1-6 PM	39.6	42.8	46.5	49.7	49.7
	Nov	4-9 PM	26.9	29.3	31.9	34.0	34.0
	Dec	4-9 PM	20.4	22.2	24.0	25.3	25.3

Table 4-8 shows how the aggregate August monthly peak load impacts vary as a function of the switch success rate that is ultimately realized in August 2014. As with any forecast, unforeseen factors may result in a switch success rate that is higher or lower than expected. If SCE reaches its forecast target of a 95% switch success rate by August 2014, the aggregate 1-in-2 load impact is 46.6 MW and the 1-in-10 result is 48.5 MW. However, if the switch success rate stays at 83%, the 1-in-2 and 1-in-10 load impacts are 15% lower. These results assume that the projected enrollment of 990 customers by August 2014 is achieved, which is another key variable that can be affected by unforeseen factors. It is also assumed that new participants are similar to the existing population in terms of usage. If new participants are significantly larger or smaller than the existing AP-I population, the aggregate load impacts will be higher or lower than expected, even if the 990 customer target is achieved. All of these factors – switch success rates, enrollment and the size of new participants – must be tracked closely to ensure that SCE reaches the expected MW level of load impacts that is presented in this ex ante analysis.

Table 4-8:
AP-I Aggregate 2014 August Monthly Peak Load Impacts (MW)
by August 2014 Switch Success Rate

Switch Success Rate (August 2014)	Aggregate 2014 August Monthly Peak Load Impacts (MW)	
	1-in-2	1-in-10
80%	39.2	40.9
83% (Current)	40.7	42.4
86%	42.1	43.9
89%	43.6	45.5
92%	45.1	47.0
95% (Forecast)	46.6	48.5
98%	48.0	50.1

4.6 AP-I Recommendations

As discussed in Section 4.5, future AP-I aggregate load impacts are closely tied to switch success rates, enrollment and the size of new participants. By August 2014, SCE expects to:

- Improve the switch success rate from 83% to 95%;
- Increase AP-I enrollment from 802 to 990 participants; and
- Enroll new participants that have similar usage to the existing AP-I population.

All of these factors must be tracked closely to ensure that SCE reaches the expected MW level of load impacts that is presented in the ex ante analysis.

As discussed in last year's evaluation, we recommend improving the switch success rate though the following steps:

1. Run tests or actual events during the summer, when pumps are on. Ideally, the test event would occur during peak hours and last long enough to determine whether pumps that were operating immediately before the event ramped down when the event signal was sent to the switches;
2. Analyze the 15 minute interval data to identify units that were on immediately prior to the event but were not activated. The criteria for determining activation must factor in that some pumps ramp down over five minutes and that additional loads not controlled by switches are measured by the same meter for a small fraction of participants; and
3. Target the identified accounts for a switch activation inspection and repair, as appropriate.

Calling events facilitates the ability to identify pumps that are not providing load reduction and improve the switch success rates. Out of necessity, the improvement in switch success rates would be conducted over the course of two or three years. It takes time to call events, identify units that are not providing load reduction, inspect and repair. Moreover, not all units will be on for a given event due to the variable nature of pump loads. As a result, the process is an iterative one.

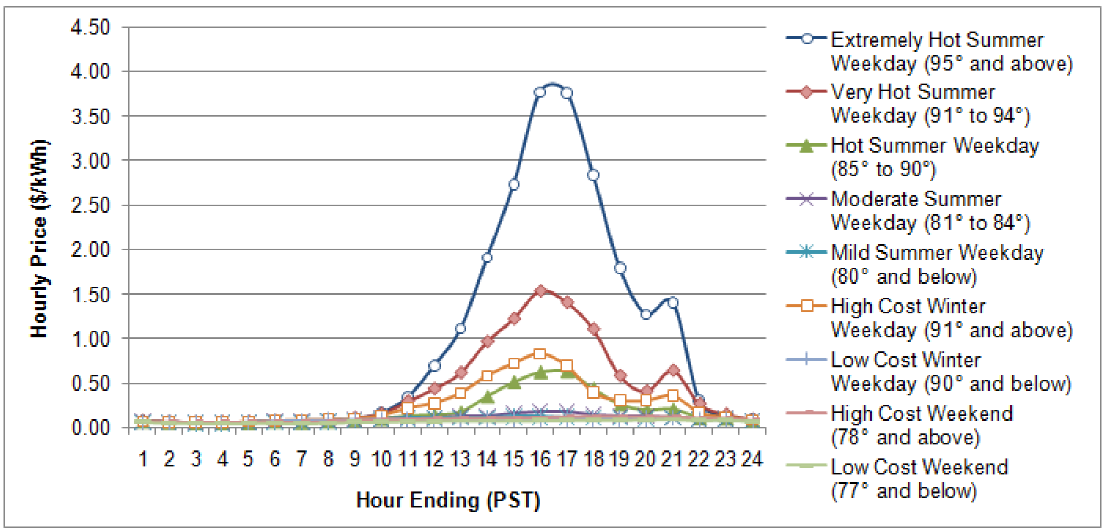
5 Real Time Pricing Program

This section contains the RTP program background and history, analysis methodology, ex post load impact estimates, ex ante load impact estimates and recommendations.

5.1 RTP Program Background and History

The Real Time Pricing (Schedule RTP-2 or RTP) program is a dynamic pricing tariff that charges participants for the electricity they consume based on hourly prices that vary according to day type and temperature. It attempts to incorporate both the time-varying components of energy costs and generation capacity costs. The RTP tariff consists of nine hourly pricing profiles that vary by season, day type and a range of temperatures measured at the Los Angeles Civic Center (downtown LA) on the previous day (see Figure 5-1). The tariff is available to large commercial and industrial customers (i.e., customers eligible for service under Schedule TOU-8). Because the rate schedules are linked to variation in weather, participants experience more high-price days during extreme weather years than in normal weather years.

Figure 5-1:
2010 RTP Hourly Price Profiles by Schedule
(2 kV and Below[12])



In compliance with the CPUC guidance on dynamic pricing, the RTP prices were recently revised in October 2009. The rate redesign follows the CPUC's guidance on dynamic rates and represents a significant increase in the peak-period prices faced by RTP customers on extremely hot summer weekdays, high cost winter weekdays and very hot summer weekdays. On an extremely hot summer weekday (when the downtown LA temperature is 95°F or above on the previous day), the current RTP price peaks at $3.77/kWh from 4 PM to 6 PM. Previously, the maximum price on an extremely hot summer weekday was around $2.25/kWh (40% lower). The increases are offset by lower rates during off-

12 The applicable price schedules vary slightly for customers connected at less than 2kV, 2kV to 50kV and greater than 50kV.

peak hours. Overall, the peak to off-peak price ratio for the redesigned tariff is substantially larger and encourages load shifting from peak periods to off-peak periods, particularly during high-price days.[13]

The RTP program was closed to new enrollment in 1998 with the implementation of the deregulated market structure, but opened again in January 2008. In the beginning of 2011, there were 101 enrolled accounts on the RTP tariff. Enrollment grew from 84 accounts in 2009. Many of the new enrollees were customers that were defaulted on to CPP, but were offered RTP as an opt-out tariff. Although RTP has grown in the past year, the aggregate program load is still dominated by a few very large manufacturing customers in the LA Basin local capacity area (LCA). The three largest participants account for 73% of total program load. Across all customers, the manufacturing sector in the LA Basin LCA accounts for 90% of total program load.

RTP is expected to experience continued enrollment growth over the next few years because SCE plans to make the program available to all C&I customers, regardless of size.[14] In August 2013, RTP enrollment is expected to equal 184 participants and by August 2014, enrollment is expected to equal 268. Afterwards, enrollment is assumed to remain constant until the end of the ex ante forecast period (2021).[15] Although program enrollment is expected to more than double, the ex ante impacts will grow relatively less because it is expected that many new enrollees will be smaller than the average existing RTP cusotmer.

5.2 RTP Analysis Methodology

The ex post and ex ante load impact estimates are based on individual customer regressions. The regression models were estimated on load data from 2008 to 2010 and used to predict load based on RTP prices and the otherwise applicable tariff (OAT), which is TOU-8 option B. The load impacts are the difference between demand in each hour with and without RTP prices in effect. Since different price schedules are in effect on a daily basis, estimating customer response to prices is necessary for determining RTP impacts. After the model was estimated, demand impacts associated with each rate schedule were estimated by comparing predicted load based on the RTP price with predicted load based on the OAT.

The load impacts for all customers are determined by the price schedules in effect on a given day. Table 5-1 shows the historical frequency of the different price schedules for 2008 through 2010. During this time period, there were 11 extremely hot summer weekdays when the highest prices were in effect. The low cost winter weekday is the most common price schedule, occurring on 44% of days from 2008 to 2010. Although high-price days are infrequent, there is sufficient variation in the 2008 to 2010 time period from which to model how load responds to RTP prices.

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13 Although RTP does not have specific peak and off-peak hours like a TOU rate, similar terminology is used to describe the rate (i.e., "peak period" refers to 1 PM to 6 PM and "off-peak period" refers to other hours).

14 Currently, RTP is only available to C&I customers above 200 kW.

15 Stephen George and Josh Bode. "Enrollment Projections and Load Impacts for SCE's Demand Response and Dynamic Pricing Programs." February 23, 2011. (Prepared by FSC for SCE in conjunction with its 2012-2014 DR Application)

Table 5-1:
Historical Frequency of RTP Price Schedules by Year

RTP Price Schedule	2008	2009	2010
1. Extremely Hot Summer Weekday (95° F & above)	1	6	4
2. Very Hot Summer Weekday (91° to 94° F)	2	5	7
3. Hot Summer Weekday (85° to 90° F)	21	16	7
4. Moderate Summer Weekday (81° to 84° F)	33	18	10
5. Mild Summer Weekday (80° F & below)	28	42	58
6. High Cost Winter Weekday (91° F & above)	13	5	4
7. Low Cost Winter Weekday (90° F & below)	156	162	164
8. High Cost Summer/Winter Weekend (78° F & above)	59	49	40
9. Low Cost Summer/Winter Weekend (77° F & below)	53	62	71
Total	**366**	**365**	**365**

5.2.1 RTP Model Development

The final regression models were estimated using individual customer time series data. The dependent variable in the model is the average hourly demand. In most electricity pricing models, the natural logarithm of price is the functional form used to explain how load responds to price. This functional form was tested extensively, but it was found that price and price squared more accurately captured how RTP customer load responds to price variation. Price and price squared are interacted with hour for the 12 noon to 10 PM time period, which is when there is substantial price variation. From 10 PM to 11 AM, RTP prices are consistently low and do not vary substantially, which is why it is unnecessary to include hourly price variables for that time period. The price ratio variable is interacted with all hours of the day because it varies substantially depending on the maximum price for the day. It also captures load shifting to hours when prices are relatively low.

Considering that the RTP price schedule varies with temperature, it is important that pricing effects are not confounded with the weather variables. Therefore, weather variables are not included for manufacturing customers, which are not sensitive to changes in temperature. Large manufacturing facilities may have some usage related to heating or cooling, but it is likely an insignificant portion of the overall load. In RTP, manufacturing customers have an average load of 2.3 MW, whereas the other industries average less than 0.5 MW. For these smaller non-manufacturing facilities, the weather variables are included.

Mathematically, the regression can be expressed by:

$$kW_t = A + \sum_{i=13}^{22} B_i \times Hour_i \times Price_t + \sum_{i=13}^{22} C_i \times Hour_i \times PriceSQR_t$$
$$+ \sum_{i=1}^{24} D_i \times Hour_i \times PriceRatio_t + \sum_{i=1}^{24}\sum_{j=1}^{5} E_{ij} \times Hour_i \times DayType_j$$
$$+ \sum_{j=2}^{12} F_j \times Month_j + \sum_{i=1}^{24} G_i \times Hour_i \times Year2010_t$$
$$+ \sum_{i=1}^{24} H_i \times Hour_i \times BIP\_EventDay_t + e_t$$

For non-manufacturing customers, the following weather variables were also included:

$$+ \sum_{i=1}^{24} I_{ij} \times Hour_i \times TotalCDH_t + \sum_{i=1}^{24} J_{ij} \times Hour_i \times TotalHDH_t$$

Table 5-2:
Description of Variables

Variable	Description
kW_t	hourly RTP customer load at time t
A	estimated constant term
B_i through J_{ij}	estimated parameters
$Hour_i$	series of binary variables for each hour
$Price_t$	RTP price in effect for each hour
$PriceSQR_t$	RTP price squared
$PriceRatio_t$	ratio between the RTP price in effect for each hour and the maximum price for the day, which captures load shifting to hours when prices are relatively low
$DayType_j$	series of binary variables representing five different day types (Mon, Tues-Thurs, Fri, Sat, Sunday/Holiday)
$Month_j$	series of binary variables for each month
$Year2010_t$	binary variable for the most recent year of load data
$BIP\_Eventday_t$	binary variable for dually-enrolled customers that participated in the 2009 BIP event
$TotalCDH_t$	total number of cooling degree hours (base 70) per day
$TotalHDH_t$	total number of heating degree hours (base 70) per day
e_t	error term

5.2.2 RTP Model Accuracy and Validity Assessment

Given that load impacts are calculated as the difference between hourly usage on RTP and the OAT, it is important that the model predicts accurately at many different price levels.

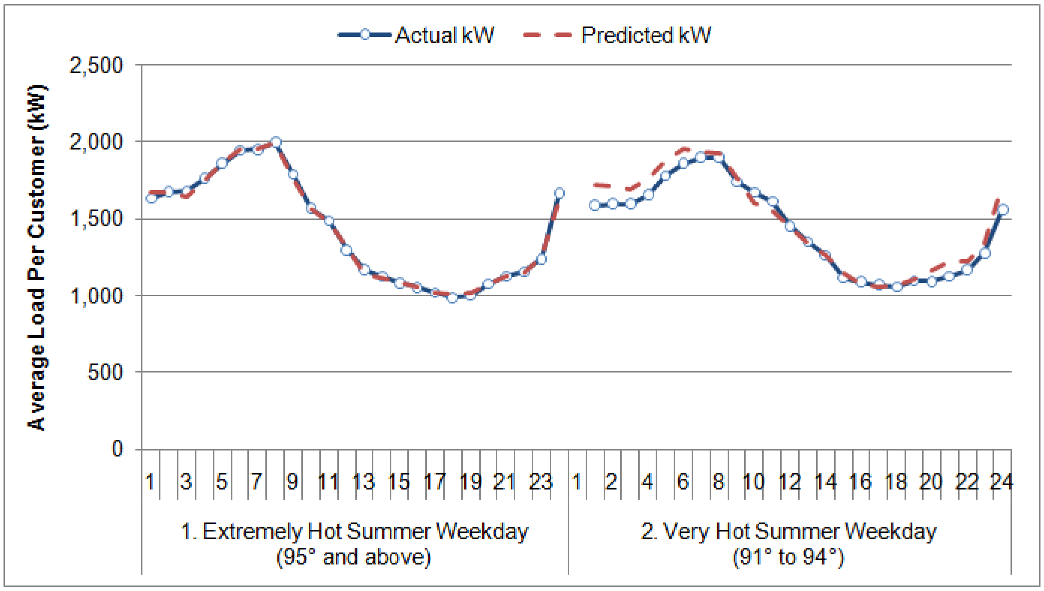
Out-of-sample Validation

With the new RTP prices that came into effect in 2010, the model validation focused on predicted and actual load by price schedule over the past year. In the first test of model accuracy, a series of out-of-sample validations was conducted. Rather than running the model on all of the available load data, one day from each of the five summer weekday pricing profiles was randomly selected to be withheld from the estimation. Although these five days are not included in the estimating sample, the model is used to predict load on those days. This process is repeated four times so that out-of-sample predictions of load are generated for 20 summer weekdays (4 days from each summer weekday pricing schedule). Considering that there were four extremely hot summer weekdays in 2010, this method provided out-of-sample predictions for each of the days when prices were highest; which is when the model must be accurate.

This validation process most closely aligns with what is expected of the model in the ex post and ex ante analyses. In the ex ante analysis, the model is used to simulate the reference load and estimated load with DR under 1-in-2 and 1-in-10 weather year scenarios. The ex post analysis estimates load reductions by predicting load if the customer was on the OAT. In both of these analyses, out-of-sample predictions are generated for scenarios in which actual, unperturbed load is not available. Therefore, out-of-sample validation using randomly selected summer weekdays is a very good test to determine which model is most accurate.

Figure 5-2 shows the results of the out-of-sample validation for the two summer weekday schedules with the highest prices. As seen in the figure, the model accurately predicts load at high prices even if those days are not included in the estimating sample. On the extremely hot summer weekdays when prices are highest, the difference between actual and predicted load did not exceed 3% in any hour. More importantly, the percentage error is lowest during the middle hours of the day when prices are as high as $3.77/kWh. Between 1 PM and 6 PM during the extremely hot summer weekdays, the percentage error is only 0.4%. On the very hot summer weekdays, the model over predicts by 3% on average throughout the day, but the percentage error is only 0.2% between 1 PM and 6 PM.

Figure 5-2:
Actual v. Predicted Average Load by Price Schedule
Out-of-Sample Validation

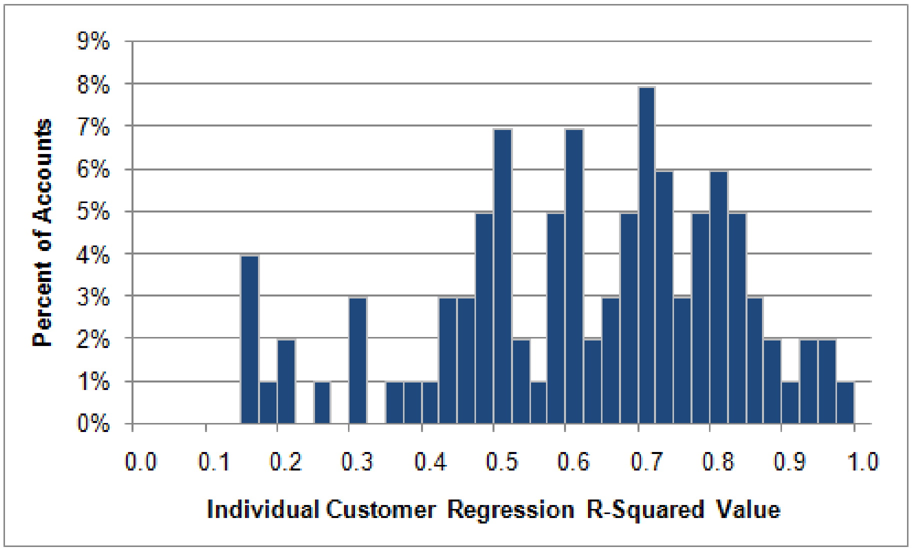


Goodness of Fit Measures

Although the regressions were estimated at the individual customer level, from a policy standpoint, the focus is less on how the regressions perform for individual customers than it is on how the regressions perform for the average participant and for specific customer segments. Overall, individual customers exhibited more variation and less consistent energy use patterns than the aggregate participant population. Likewise, the regressions are better at explaining the variation in electricity consumption and load impacts for the average customer (or average customer within a specific segment) than for individual customers. Put differently, it is more difficult to fully explain how a customer from a specific industry behaves on an hourly basis than it is to explain how the average customer in that industry behaves on an hourly basis. Because of this, we present measures of the explained variation, as described by the R-squared goodness-of-fit statistic, for the individual regressions for specific customer segments and for the average customer overall.

Figure 5-3 shows the distribution of R-squared values from the individual customer regressions for RTP customers. Roughly half of the individual customer regressions had R-squared values above 0.65, which suggests that the model predicts well for most RTP customers. The lower one-third of all individual regressions had R-squared statistics up to 0.51.

Figure 5-3:
Distribution of R-squared Values from Individual Regressions for RTP Customers



In order to estimate the average customer R-squared values for each industry, LCA or the program as a whole, the regression-predicted and actual electricity usage values were averaged across all customers for each date and hour. This process produced regression predicted and actual values for the average customer, which enabled the calculation of errors for the average customer and the calculation of the R-squared value. The R-squared values for the average participant and for the average customer by segment were estimated using the following formula:[16]

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

Table 5-3:
Variable Description

Variable	Description
y_t	actual energy use at time t
$\hat{y}_t$	regression predicted energy use at time t
$\bar{y}$	average energy use across all time periods

Table 5-4 summarizes the amount of variation explained by the regression model by industry, LCA and for all customers overall. For all customers, the model has an aggregate R-squared value of 0.96, which

16 Technically, the R-squared value needs to be adjusted based on the number of parameters and observations from each regression. Given that the number of observations per regression was typically over 8,000, the effects of the adjustment were anticipated to be minimal. As a result, the unadjusted R-squared is presented in order to avoid the complication of tracking the number of observations and parameters from each individual regression.

means that the model explains 96% of variation in aggregate RTP load. As noted above, program load is concentrated among manufacturing customers in the LA Basin LCA. These two segments also have an aggregate R-squared value of 0.96. The remaining segments have lower R-squared values, which is expected when there are fewer customers. The lowest R-squared value is among customers in the wholesale, transport & other utilities segment (0.49). In general, customers in the wholesale, transport & other utilities segment have usage that is relatively more difficult to explain, which is why their aggregate R-squared value is relatively low.

Table 5-4:
Aggregate R-Squared Values by Industry and LCA

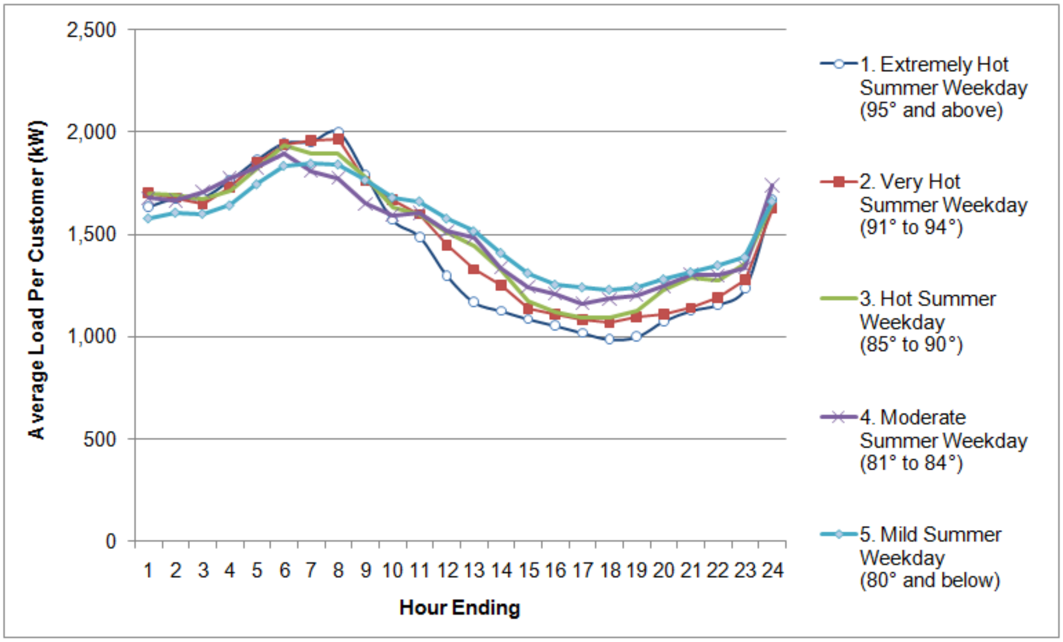
Group Type	Segment	Number of Customers	Aggregate R-Squared
Industry	Agriculture, Mining & Construction	18	0.88
	Manufacturing	61	0.96
	Wholesale, Transport & Other Utilities	10	0.49
	Offices, Hotels, Finance & Services	9	0.75
	Schools	1	0.74
	Institutional/Government	2	0.50
LCA	LA Basin	87	0.96
	Outside LA Basin	5	0.70
	Ventura	9	0.73
	Overall	**101**	**0.96**

5.3 RTP Ex Post Load Impact Estimates

The load impact protocols require that impacts for non-event based programs be developed for the average weekday for each month and for the monthly system peak day for both ex post and ex ante purposes. For the ex post analysis, the overall impacts were calculated as the difference between the regression predicted load under 2010 RTP prices and under the OAT.

Figure 5-4 shows the average load per customer for each RTP summer weekday price schedule in 2010. Although the graph does not control for differences in weather, seasonality or other factors, it reflects that customers did engage in peak load reductions and load shifting on days with higher price schedules. For example, when ranked from lowest to highest peak period load, the summer hourly load profiles follow the strength of the price signals. The extremely hot summer weekdays have lower load levels than all other price schedules. Although very hot and hot summer day loads are almost equivalent over the peak period, more load shifting is evident on very hot days, which have stronger peak to off-peak price ratios. Finally, moderate summer weekdays have the second to highest load and mild summer weekdays have the highest load.

Figure 5-4:
2010 Average Load by RTP Summer Weekday Price Schedule



On September 27, 2010, Southern California experienced a short, but intense heat wave that almost resulted in a new all-time system peak for SCE. Between 4 PM and 5 PM on September 27th, SCE system load nearly reached 23,000 MW, which had only happened once before in 2007 when system load peaked at 23,130 MW. The temperature recorded in downtown LA on the previous day was 105°F, which put the extremely hot summer weekday price schedule in effect for RTP.

Figure 5-5 shows the average estimated load impact per RTP customer in each hour on September 27th. As seen, the average load drop over the five-hour peak period from 1 PM to 6 PM was 196.6 kW. Figure 5-6 shows the aggregate load impact for each hour of the day. The aggregate load drop during the peak period was nearly 20 MW. This represents a 15.5% reduction relative to the reference load of 127 MW. As demonstrated by these results on September 27th, the RTP program performed well when it was needed most.

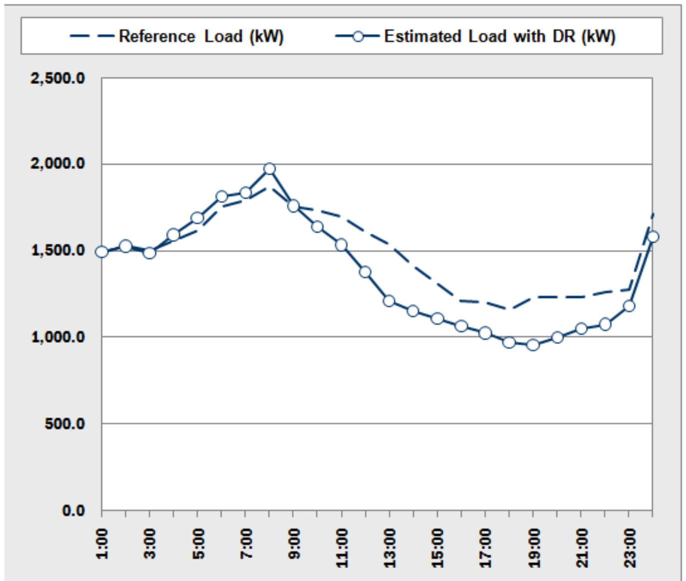
Figure 5-5:
Average RTP Ex Post Load Impact (kW) per Participant for September 27, 2010

TABLE 1: Menu options

Type of Results	Average Enrolled Account
Month	September
Day Type	System Peak Day
Customer Characteristic	All Customers

TABLE 2: Output

RTP Rate Schedule	1. Extremely Hot Summer Weekday (>=95)
Date	Monday, September 27, 2010
Number of Accounts	101
Average Load Impact (kW) (1-6pm)	196.6
% Load Impact (1-6pm)	15.5%



Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	% Load Impact	RTP Price ($/kWh)	OAT Price ($/kWh)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
								10th	30th	50th	70th	90th
1:00	1488.8	1493.6	-4.9	-0.3%	$0.08	$0.07	75.1	-270.6	-113.6	-4.9	103.9	260.9
2:00	1526.4	1525.2	1.3	0.1%	$0.07	$0.07	75.2	-255.9	-104.0	1.3	106.5	258.4
3:00	1497.8	1483.2	14.5	1.0%	$0.06	$0.07	74.8	-238.0	-88.8	14.5	117.9	267.1
4:00	1555.7	1590.8	-35.1	-2.3%	$0.06	$0.07	74.0	-289.4	-139.2	-35.1	69.0	219.3
5:00	1616.2	1690.8	-74.6	-4.6%	$0.06	$0.07	73.8	-328.4	-178.5	-74.6	29.3	179.2
6:00	1756.1	1810.5	-54.4	-3.1%	$0.06	$0.07	73.3	-309.7	-158.9	-54.4	50.0	200.8
7:00	1786.6	1832.4	-45.8	-2.6%	$0.07	$0.07	75.7	-302.9	-151.0	-45.8	59.4	211.3
8:00	1873.4	1972.2	-98.8	-5.3%	$0.07	$0.07	81.0	-366.7	-208.4	-98.8	10.8	169.1
9:00	1757.2	1758.2	-0.9	-0.1%	$0.08	$0.13	87.0	-245.2	-100.9	-0.9	99.1	243.4
10:00	1729.3	1637.9	91.4	5.3%	$0.10	$0.13	94.1	-147.9	-6.6	91.4	189.3	330.7
11:00	1694.4	1533.5	161.0	9.5%	$0.16	$0.13	99.9	-76.3	63.9	161.0	258.0	398.2
12:00	1611.7	1377.2	234.6	14.6%	$0.33	$0.13	103.8	0.8	138.9	234.6	330.2	468.4
13:00	1539.1	1209.5	329.5	21.4%	$0.68	$0.30	104.4	96.3	234.1	329.5	425.0	562.8
14:00	1412.3	1153.1	259.2	18.4%	$1.09	$0.30	104.4	28.4	164.7	259.2	353.6	490.0
15:00	1314.6	1107.4	207.2	15.8%	$1.87	$0.30	103.9	-21.4	113.7	207.2	300.8	435.8
16:00	1211.0	1064.3	146.8	12.1%	$2.67	$0.30	102.4	-81.1	53.5	146.8	240.0	374.6
17:00	1204.2	1025.2	179.0	14.9%	$3.68	$0.30	100.6	-49.2	85.6	179.0	272.4	407.2
18:00	1160.6	969.8	190.8	16.4%	$3.67	$0.30	97.0	-38.5	97.0	190.8	284.6	420.1
19:00	1232.5	958.1	274.4	22.3%	$2.77	$0.13	92.8	44.9	180.5	274.4	368.4	504.0
20:00	1232.4	1000.6	231.8	18.8%	$1.75	$0.13	88.0	2.7	138.1	231.8	325.6	460.9
21:00	1235.3	1049.4	185.9	15.1%	$1.24	$0.13	84.0	-43.5	92.1	185.9	279.8	415.3
22:00	1259.7	1075.5	184.2	14.6%	$1.37	$0.13	82.0	-46.1	89.9	184.2	278.4	414.4
23:00	1276.1	1183.0	93.1	7.3%	$0.30	$0.13	80.0	-140.5	-2.5	93.1	188.6	326.6
0:00	1707.2	1578.4	128.8	7.5%	$0.11	$0.07	79.1	-121.5	26.4	128.8	231.3	379.2
	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Chage in Energy Use	Daily Average RTP Price	Daily Average OAT Price	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
								10th	30th	50th	70th	90th
Daily	35,678.6	33,079.6	2,599.0	7.3%	$0.93	$0.15	426.2	1413.6	2113.9	2599.0	3084.0	3784.4

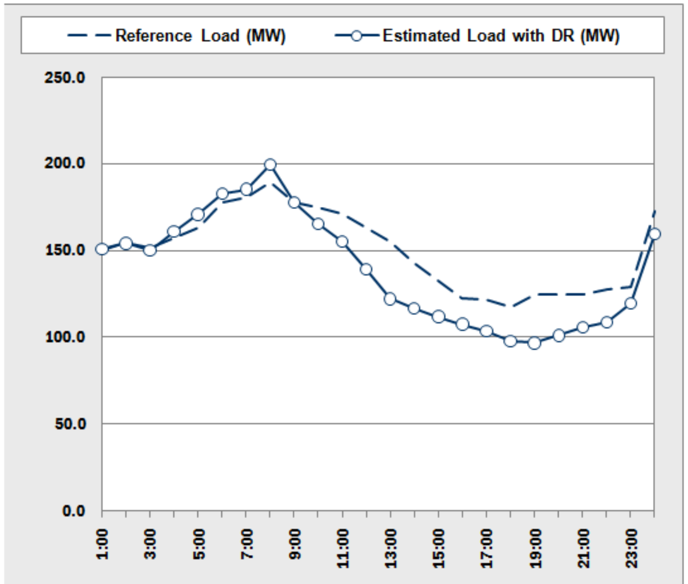
Figure 5-6:
Aggregate RTP Ex Post Load Impact (MW) for September 27, 2010

TABLE 1: Menu options

Type of Results	Aggregate
Month	September
Day Type	System Peak Day
Customer Characteristic	All Customers

TABLE 2: Output

RTP Rate Schedule	1. Extremely Hot Summer Weekday (>=95)
Date	Monday, September 27, 2010
Number of Accounts	101
Average Load Impact (MW) (1-6pm)	19.9
% Load Impact (1-6pm)	15.5%



Hour Ending	Reference Load (MW)	Estimated Load with DR (MW)	Load Impact (MW)	% Load Impact	RTP Price ($/kWh)	OAT Price ($/kWh)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	150.4	150.9	-0.5	-0.3%	$0.08	$0.07	75.1	-27.3	-11.5	-0.5	10.5	26.4
2:00	154.2	154.0	0.1	0.1%	$0.07	$0.07	75.2	-25.8	-10.5	0.1	10.8	26.1
3:00	151.3	149.8	1.5	1.0%	$0.06	$0.07	74.8	-24.0	-9.0	1.5	11.9	27.0
4:00	157.1	160.7	-3.5	-2.3%	$0.06	$0.07	74.0	-29.2	-14.1	-3.5	7.0	22.1
5:00	163.2	170.8	-7.5	-4.6%	$0.06	$0.07	73.8	-33.2	-18.0	-7.5	3.0	18.1
6:00	177.4	182.9	-5.5	-3.1%	$0.06	$0.07	73.3	-31.3	-16.0	-5.5	5.1	20.3
7:00	180.4	185.1	-4.6	-2.6%	$0.07	$0.07	75.7	-30.6	-15.3	-4.6	6.0	21.3
8:00	189.2	199.2	-10.0	-5.3%	$0.07	$0.07	81.0	-37.0	-21.0	-10.0	1.1	17.1
9:00	177.5	177.6	-0.1	-0.1%	$0.08	$0.13	87.0	-24.8	-10.2	-0.1	10.0	24.6
10:00	174.7	165.4	9.2	5.3%	$0.10	$0.13	94.1	-14.9	-0.7	9.2	19.1	33.4
11:00	171.1	154.9	16.3	9.5%	$0.16	$0.13	99.9	-7.7	6.5	16.3	26.1	40.2
12:00	162.8	139.1	23.7	14.6%	$0.33	$0.13	103.8	0.1	14.0	23.7	33.4	47.3
13:00	155.4	122.2	33.3	21.4%	$0.68	$0.30	104.4	9.7	23.6	33.3	42.9	56.8
14:00	142.6	116.5	26.2	18.4%	$1.09	$0.30	104.4	2.9	16.6	26.2	35.7	49.5
15:00	132.8	111.8	20.9	15.8%	$1.87	$0.30	103.9	-2.2	11.5	20.9	30.4	44.0
16:00	122.3	107.5	14.8	12.1%	$2.67	$0.30	102.4	-8.2	5.4	14.8	24.2	37.8
17:00	121.6	103.5	18.1	14.9%	$3.68	$0.30	100.6	-5.0	8.6	18.1	27.5	41.1
18:00	117.2	98.0	19.3	16.4%	$3.67	$0.30	97.0	-3.9	9.8	19.3	28.7	42.4
19:00	124.5	96.8	27.7	22.3%	$2.77	$0.13	92.8	4.5	18.2	27.7	37.2	50.9
20:00	124.5	101.1	23.4	18.8%	$1.75	$0.13	88.0	0.3	13.9	23.4	32.9	46.6
21:00	124.8	106.0	18.8	15.1%	$1.24	$0.13	84.0	-4.4	9.3	18.8	28.3	41.9
22:00	127.2	108.6	18.6	14.6%	$1.37	$0.13	82.0	-4.7	9.1	18.6	28.1	41.9
23:00	128.9	119.5	9.4	7.3%	$0.30	$0.13	80.0	-14.2	-0.3	9.4	19.1	33.0
0:00	172.4	159.4	13.0	7.5%	$0.11	$0.07	79.1	-12.3	2.7	13.0	23.4	38.3
	Reference Energy Use (MWh)	Energy Use with DR (MWh)	Change in Energy Use (MWh)	% Chage in Energy Use	Daily Average RTP Price	Daily Average OAT Price	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	3,603.5	3,341.0	262.5	7.3%	$0.93	$0.15	426.2	142.8	213.5	262.5	311.5	382.2

Table 5-5 shows the average and aggregate ex post load impact estimates for the 1 PM to 6 PM window for each monthly system peak day in 2010.[17] The ex post impacts vary substantially as a function of the underlying RTP rates. For the monthly system peak days from October through May, the low cost winter weekday price schedule was in effect. When this price schedule was in effect, there was a small negative impact because RTP prices were relatively lower than the OAT from 1 PM to 6 PM compared to later in the day. Therefore, RTP customers shift a small amount of load to the 1 PM to 6 PM time period on low cost winter weekdays. For the June system peak, the mild summer weekday price schedule was in effect. On this day, the load impact was negative because on-peak RTP prices were around $0.12/kWh versus $0.29/kWh on the OAT. As noted above, the RTP program produced a significant load reduction when it was needed most on September 27th. The program also reduced load on the July and August system peak days when the very hot summer weekday price schedule was activated. On these days, the average load reduction was around 135 kW per customer and 13.6 MW in aggregate, with a percent load impact of 10.5%. As expected, the load impacts were not as high as the September peak, but substantial nonetheless.

Table 5-5:
2010 Average and Aggregate RTP Ex Post Load Impact Estimates
Monthly System Peak Days, On-Peak Period (1 PM to 6 PM)

Monthly System Peak Date	Price Schedule	Number of Customers	Avg. Reference Load (kW)	Avg. Load with DR (kW)	Avg. Load Reduction (kW)	Aggregate Load Reduction (MW)
Oct 16, 2009	7. Low Cost Winter Weekday	74	1,404.2	1,417.3	-13.1	-1.0
Nov 3, 2009	7. Low Cost Winter Weekday	74	1,453.9	1,466.3	-12.4	-0.9
Dec 8, 2009	7. Low Cost Winter Weekday	75	1,434.1	1,446.4	-12.3	-0.9
Jan 20, 2010	7. Low Cost Winter Weekday	77	1,385.5	1,397.6	-12.1	-0.9
Feb 9, 2010	7. Low Cost Winter Weekday	77	1,329.7	1,341.9	-12.1	-0.9
Mar 17, 2010	7. Low Cost Winter Weekday	78	1,216.8	1,228.6	-11.8	-0.9
Apr 26, 2010	7. Low Cost Winter Weekday	82	1,084.8	1,098.3	-13.5	-1.1
May 20, 2010	7. Low Cost Winter Weekday	87	1,054.0	1,067.7	-13.7	-1.2
Jun 30, 2010	5. Mild Summer Weekday	97	1,276.1	1,310.9	-34.8	-3.4
Jul 16, 2010	2. Very Hot Summer Weekday	100	1,300.3	1,164.7	135.7	13.6
Aug 25, 2010	2. Very Hot Summer Weekday	101	1,250.2	1,115.4	134.9	13.6
Sep 27, 2010	1. Extremely Hot Summer Weekday	101	1,260.5	1,063.9	196.6	19.9

Table 5-6 shows the average and aggregate ex post load impact estimates for the 1 PM to 6 PM window on the average weekday for each month. The average weekday impacts depend on the frequency and mix of RTP price schedules within each month. From November 2009 to May 2010, the temperature in downtown LA did not rise above 90°F, so the low cost winter weekday price schedule was in effect for

[17] As in last year's evaluation, load data is only available through September of the evaluation year. Therefore, 2009 monthly system peak days are used for October through December.

every weekday. As such, the load reduction was slightly negative on the average weekday for those months. June had relatively low temperatures in 2010 and the mild summer weekday price schedule was in effect for all but two weekdays. The average on-peak RTP price in June 2010 was nearly 60% lower than the OAT, which explains why the impacts were substantially negative. The average weekday load reduction was largest in August 2010, when the maximum temperature in downtown LA rose above 85°F on 8 out of 22 weekdays. September 2010 had three consecutive extremely hot summer weekdays during the short heat wave at the end of the month, but the remaining days were relatively mild. Although the average weekday load impacts were negative during most months, the program delivered load reductions when temperatures and RTP prices rose in August and September of 2010.

Table 5-6:
2010 Average and Aggregate RTP Ex Post Load Impact Estimates
Average Weekday by Month, On-Peak Period (1 PM to 6 PM)

Month	Number of Customers	Avg. Reference Load (kW)	Avg. Load with DR (kW)	Avg. Load Reduction (kW)	Aggregate Load Reduction (MW)
October 2009	74	1,405.9	1,409.7	-3.8	-0.3
November 2009	75	1,398.3	1,409.1	-10.8	-0.8
December 2009	75	1,408.5	1,420.7	-12.2	-0.9
January 2010	77	1,360.1	1,372.1	-12.0	-0.9
February 2010	77	1,298.0	1,309.2	-11.3	-0.9
March 2010	78	1,205.4	1,217.0	-11.6	-0.9
April 2010	81	1,122.0	1,134.9	-12.9	-1.0
May 2010	85	1,055.3	1,068.1	-12.8	-1.1
June 2010	95	1,308.8	1,343.6	-34.8	-3.3
July 2010	100	1,206.8	1,213.5	-6.7	-0.7
August 2010	101	1,258.7	1,237.5	21.1	2.1
September 2010	101	1,216.5	1,209.4	7.1	0.7

5.4 RTP Ex Ante Load Impact Estimates

RTP grew from 84 to 101 accounts from September 2009 to September 2010. The program is expected to experience continued enrollment growth over the next few years because SCE plans to make the program available to all C&I customers, regardless of size. In August 2013, RTP enrollment is expected to equal 184 participants and by August 2014, enrollment is expected to equal 268. Afterwards, enrollment is assumed to remain constant until the end of the ex ante forecast period (2021).[18]

For ex ante purposes, load impacts for existing customers are not projected to change over the forecast horizon (2011-2021). However, new participants are expected to be relatively small compared to the

[18] Stephen George and Josh Bode. "Enrollment Projections and Load Impacts for SCE's Demand Response and Dynamic Pricing Programs." February 23, 2011. (Prepared by FSC for SCE in conjunction with its 2012-2014 DR Application)

average existing customer in the program. Therefore, load impacts for the two largest existing RTP customers are not included in the estimation of expected load reductions for new participants. These two large customers have average loads of over 25 MW and are unlikely to be representative of new participants.

Although removing the two largest customers from the estimation of load reductions for new participants will lead to a more conservative estimate, there are several unknown factors that could significantly change the result. For example, if new participants are substantially smaller than the average existing RTP customer, the resulting aggregate load reduction will be relatively lower. On the other hand, if SCE is able to successfully market RTP and recruit more large customers over 25 MW, the resulting aggregate load reduction will be relatively higher. Considering that enrollment is expected to nearly triple over the next four years, there is a lot of uncertainty in the future load impacts. Nonetheless, the ex ante impacts presented here are the best estimates given the available data.

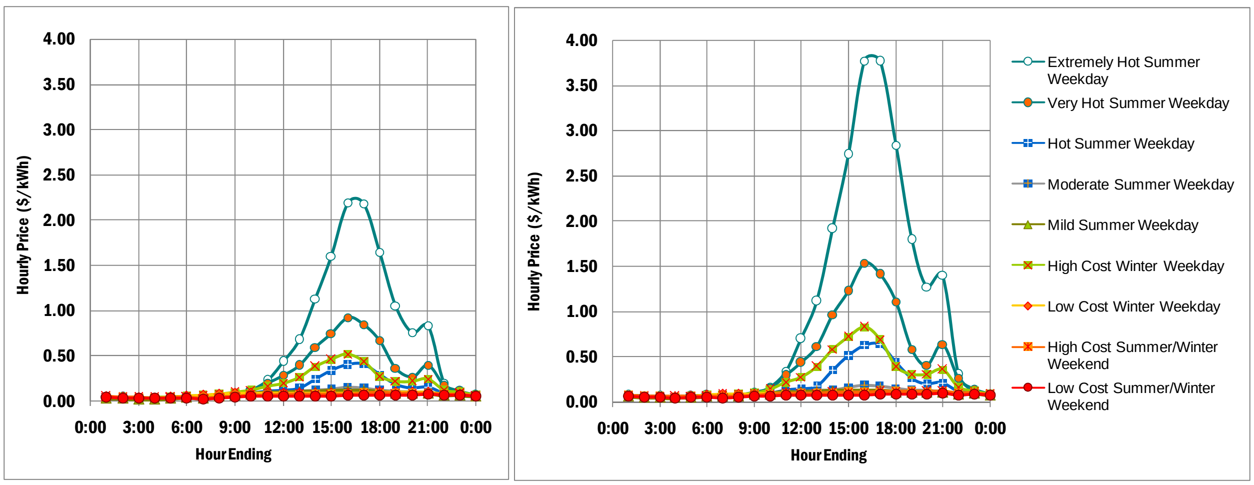
The 1-in-2 and 1-in-10 system load conditions were matched with the RTP price schedules based on the prior day's maximum temperature in downtown LA. This approach was employed to accurately reflect the method for selecting the price schedule. Table 5-7 summarizes the price schedules in effect for each monthly system peak under 1-in-2 and 1-in-10 conditions. For summer monthly system peak days, price schedules with larger peak to off-peak price ratios are typically in effect. However, the price schedule with the strongest price signal does not always align with the monthly system peak.

Table 5-7:
RTP Price Schedule in Effect for each Ex Ante Monthly System Peak Day

Month	1-in-2 System Conditions	1-in-10 System Conditions
Jan	Low Cost Winter Weekday (90° F & below)	Low Cost Winter Weekday (90° F & below)
Feb	Low Cost Winter Weekday (90° F & below)	Low Cost Winter Weekday (90° F & below)
Mar	Low Cost Winter Weekday (90° F & below)	High Cost Winter Weekday (91° F & above)
Apr	Low Cost Winter Weekday (90° F & below)	Low Cost Winter Weekday (90° F & below)
May	Low Cost Winter Weekday (90° F & below)	High Cost Winter Weekday (91° F & above)
Jun	Mild Summer Weekday (80° F & below)	Extremely Hot Summer Weekday(95° F & above)
Jul	Hot Summer Weekday (85° to 90° F)	Hot Summer Weekday (85° to 90° F)
Aug	Very Hot Summer Weekday (91° to 94° F)	Extremely Hot Summer Weekday(95° F & above)
Sep	Extremely Hot Summer Weekday (95° F & above)	Extremely Hot Summer Weekday(95° F & above)
Oct	High Cost Winter Weekday (91° F & above)	High Cost Winter Weekday (91° F & above)
Nov	High Cost Winter Weekday (91° F & above)	Low Cost Winter Weekday (90° F & below)
Dec	Low Cost Winter Weekday (90° F & below)	Low Cost Winter Weekday (90° F & below)

For the ex ante impact analysis, the RTP and OAT rates were assumed to remain similar to the most recently filed SCE tariffs. In compliance with the CPUC guidance on dynamic pricing, the RTP prices were recently revised in October 2009. Figure 5-7 shows the difference between the previous RTP price schedule and the revised RTP price schedule. The rate redesign follows the CPUC's guidance on dynamic rates and represents a significant increase in the peak-period prices faced by RTP customers on extremely hot summer weekdays, high cost winter weekdays and very hot summer weekdays. On an extremely hot summer weekday (when the downtown LA temperature is 95°F or above on the previous day), the current RTP price peaks at $3.77/kWh from 4 PM to 6 PM. Previously, the maximum price on an extremely hot summer weekday was around $2.25/kWh (40% lower). The increases are offset by lower rates during off-peak hours. Overall, the peak to off-peak price ratio for the revised tariff is substantially larger and encourages load shifting from the peak periods to the off-peak periods, particularly during high-rate days.

Figure 5-7:
Comparison of Previous and Revised RTP Hourly Price Schedules
(2 kV and Below[19])



Figures 5-8 and 5-9 show the estimated reference load and the predicted load after customers respond to RTP prices for the average customer on a typical event day based on 1-in-2 and 1-in-10 year weather conditions for the year 2014. Impacts are reported for 2014 because it is the year in which enrollment growth reaches a steady state. As seen in the figures, for a 1-in-2 typical event day, the estimated load impact is 101 kW from 1 PM to 6 PM with an average price of $1.07/kWh during the peak period. The load impact is 13.6% of the reference load. For the typical event day in a 1-in-10 weather year, prices and load impacts increase. The estimated load impact is 151 kW from 1 PM to 6 PM (20.1% of the reference load) with an average price of $2.07/kWh during the peak period. In a more extreme weather year, the high price schedules are more likely to be in effect, which results in higher load impacts for the 1-in-10 weather year.

The remainder of the hourly ex ante load impact estimates that are required by the protocols for RTP, including uncertainty adjusted estimates, can be found in the electronic appendix titled, "SCE 2010 RTP Ex Ante Load Impact Tables."

[19] The applicable price schedules vary slightly for customers connected at less than 2kV, 2kV to 50kV and greater than 50kV.

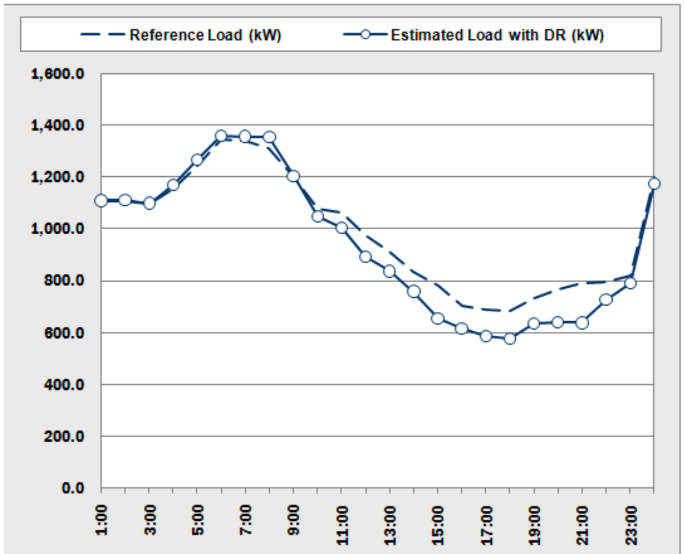
Figure 5-8:
RTP Average Load Impact (kW) per Customer in 2014
for a Typical Event Day Based on 1-in-2 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average Enrolled Account
Weather Year	1-in-2
Forecast Year	2014
Day Type	Typical Event Day
Customer Characteristic	All Customers

TABLE 2: Output

RTP Rate Schedule	N/A
Date	N/A
Number of Accounts	268
Average Load Impact (kW) (1-6pm)	101.0
% Load Impact (1-6pm)	13.6%



Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	% Load Impact	RTP Price ($/kWh)	OAT Price ($/kWh)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
1:00	1105.3	1109.1	-3.8	-0.3%	$0.08	$0.07	71.0	-204.1	-85.8	-3.8	78.2	196.5
2:00	1107.2	1111.7	-4.4	-0.4%	$0.07	$0.07	69.1	-204.3	-86.2	-4.4	77.3	195.4
3:00	1098.5	1098.4	0.2	0.0%	$0.06	$0.07	68.1	-199.2	-81.4	0.2	81.7	199.5
4:00	1154.8	1168.4	-13.6	-1.2%	$0.06	$0.07	66.8	-213.1	-95.3	-13.6	68.0	185.8
5:00	1242.7	1267.5	-24.9	-2.0%	$0.05	$0.07	66.2	-224.4	-106.5	-24.9	56.8	174.7
6:00	1343.3	1359.2	-15.9	-1.2%	$0.06	$0.07	65.4	-215.7	-97.6	-15.9	65.8	183.8
7:00	1338.4	1356.1	-17.7	-1.3%	$0.07	$0.07	64.9	-217.4	-99.4	-17.7	64.0	181.9
8:00	1310.4	1354.8	-44.5	-3.4%	$0.06	$0.07	65.4	-245.3	-126.6	-44.5	37.7	156.4
9:00	1196.4	1203.0	-6.5	-0.5%	$0.07	$0.13	68.8	-205.1	-87.8	-6.5	74.8	192.1
10:00	1077.1	1049.5	27.6	2.6%	$0.09	$0.13	74.2	-169.3	-52.9	27.6	108.2	224.5
11:00	1060.6	1003.0	57.6	5.4%	$0.13	$0.13	79.4	-139.5	-23.1	57.6	138.2	254.7
12:00	977.2	893.1	84.1	8.6%	$0.21	$0.13	83.6	-112.9	3.5	84.1	164.7	281.1
13:00	913.5	837.0	76.5	8.4%	$0.34	$0.30	86.6	-123.1	-5.2	76.5	158.2	276.2
14:00	836.5	758.6	77.9	9.3%	$0.49	$0.30	88.9	-121.5	-3.7	77.9	159.4	277.2
15:00	782.5	655.6	126.9	16.2%	$0.82	$0.30	90.6	-71.1	45.9	126.9	207.9	324.9
16:00	705.1	615.8	89.3	12.7%	$1.12	$0.30	91.0	-108.7	8.3	89.3	170.3	287.2
17:00	690.3	587.7	102.6	14.9%	$1.48	$0.30	91.1	-95.4	21.6	102.6	183.6	300.6
18:00	685.7	577.4	108.3	15.8%	$1.45	$0.30	90.1	-89.8	27.2	108.3	189.4	306.5
19:00	731.4	636.4	95.0	13.0%	$1.10	$0.13	87.9	-103.4	13.8	95.0	176.2	293.4
20:00	763.7	638.2	125.5	16.4%	$0.67	$0.13	84.8	-77.5	42.5	125.5	208.6	328.5
21:00	792.4	638.0	154.4	19.5%	$0.48	$0.13	81.0	-53.8	69.2	154.4	239.5	362.5
22:00	793.3	726.2	67.1	8.5%	$0.58	$0.13	77.0	-130.9	-13.9	67.1	148.1	265.1
23:00	818.0	790.1	27.9	3.4%	$0.19	$0.13	74.6	-169.5	-52.9	27.9	108.7	225.3
0:00	1198.6	1176.0	22.6	1.9%	$0.11	$0.07	72.8	-177.1	-59.1	22.6	104.2	222.2

	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Chage in Energy Use	Daily Average RTP Price	Daily Average OAT Price	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles 10th	30th	50th	70th	90th
Daily	23,722.7	22,610.6	1,112.1	4.7%	$0.41	$0.15	204.1	135.5	712.5	1112.1	1511.8	2088.7

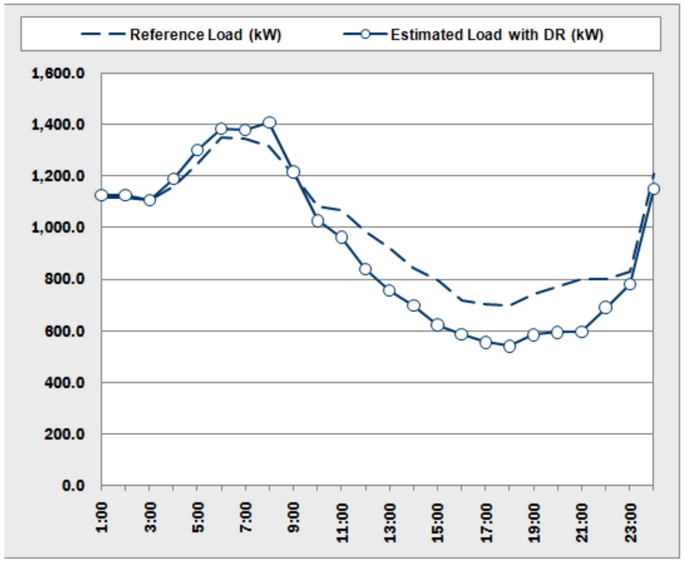
Figure 5-9:
RTP Average Load Impact (kW) per Customer in 2014
for a Typical Event Day Based on 1-in-10 Year Weather Conditions

TABLE 1: Menu options

Type of Results	Average Enrolled Account
Weather Year	1-in-10
Forecast Year	2014
Day Type	Typical Event Day
Customer Characteristic	All Customers

TABLE 2: Output

RTP Rate Schedule	N/A
Date	N/A
Number of Accounts	268
Average Load Impact (kW) (1-6pm)	151.0
% Load Impact (1-6pm)	20.1%



Hour Ending	Reference Load (kW)	Estimated Load with DR (kW)	Load Impact (kW)	% Load Impact	RTP Price ($/kWh)	OAT Price ($/kWh)	Weighted Temp (F)	Uncertainty Adjusted Impact - Percentiles				
								10th	30th	50th	70th	90th
1:00	1116.2	1124.7	-8.5	-0.8%	$0.09	$0.07	73.0	-216.4	-93.6	-8.5	76.6	199.5
2:00	1117.3	1126.9	-9.6	-0.9%	$0.07	$0.07	75.7	-216.0	-94.1	-9.6	74.8	196.8
3:00	1106.4	1106.4	0.1	0.0%	$0.06	$0.07	74.4	-204.7	-83.7	0.1	83.9	204.9
4:00	1162.1	1190.6	-28.4	-2.4%	$0.06	$0.07	73.5	-233.9	-112.5	-28.4	55.6	177.0
5:00	1249.5	1301.1	-51.6	-4.1%	$0.06	$0.07	72.8	-257.3	-135.8	-51.6	32.6	154.2
6:00	1348.8	1382.1	-33.3	-2.5%	$0.06	$0.07	72.3	-239.4	-117.6	-33.3	51.0	172.7
7:00	1342.7	1380.3	-37.6	-2.8%	$0.07	$0.07	72.0	-243.5	-121.8	-37.6	46.7	168.3
8:00	1315.3	1407.5	-92.2	-7.0%	$0.07	$0.07	72.2	-302.2	-178.1	-92.2	-6.2	117.8
9:00	1202.5	1215.5	-12.9	-1.1%	$0.08	$0.13	74.8	-216.7	-96.3	-12.9	70.4	190.8
10:00	1084.2	1026.6	57.7	5.3%	$0.09	$0.13	79.1	-141.3	-23.7	57.7	139.1	256.7
11:00	1068.5	962.6	105.9	9.9%	$0.15	$0.13	83.1	-93.2	24.4	105.9	187.3	305.0
12:00	985.1	840.5	144.6	14.7%	$0.28	$0.13	86.2	-53.9	63.4	144.6	225.8	343.0
13:00	922.0	754.8	167.1	18.1%	$0.55	$0.30	88.5	-31.1	86.0	167.1	248.2	365.3
14:00	845.8	697.7	148.1	17.5%	$0.86	$0.30	90.4	-50.1	67.0	148.1	229.2	346.3
15:00	793.9	622.1	171.8	21.6%	$1.49	$0.30	92.0	-25.4	91.1	171.8	252.4	368.9
16:00	715.4	585.2	130.2	18.2%	$2.13	$0.30	92.4	-67.0	49.5	130.2	210.9	327.5
17:00	702.6	555.4	147.3	21.0%	$2.92	$0.30	91.9	-50.1	66.5	147.3	228.0	344.6
18:00	697.5	540.0	157.4	22.6%	$2.92	$0.30	90.6	-40.2	76.6	157.4	238.3	355.0
19:00	743.5	584.1	159.4	21.4%	$2.19	$0.13	88.3	-38.7	78.3	159.4	240.5	357.5
20:00	773.1	593.8	179.3	23.2%	$1.38	$0.13	85.1	-25.1	95.6	179.3	262.9	383.7
21:00	801.8	596.4	205.4	25.6%	$0.98	$0.13	80.9	-5.7	119.0	205.4	291.8	416.5
22:00	802.4	689.9	112.5	14.0%	$1.08	$0.13	77.5	-85.2	31.6	112.5	193.3	310.1
23:00	827.4	780.7	46.7	5.6%	$0.25	$0.13	75.6	-152.6	-34.9	46.7	128.3	246.1
0:00	1209.5	1151.5	57.9	4.8%	$0.11	$0.07	74.0	-150.4	-27.3	57.9	143.2	266.2
	Reference Energy Use (kWh)	Energy Use with DR (kWh)	Change in Energy Use (kWh)	% Chage in Energy Use	Daily Average RTP Price	Daily Average OAT Price	Cooling Degree Hours (Base 70)	Uncertainty Adjusted Impact - Percentiles				
								10th	30th	50th	70th	90th
Daily	23,933.6	22,216.4	1,717.2	7.2%	$0.75	$0.15	255.9	725.4	1311.3	1717.2	2123.0	2708.9

Table 5-8 shows the aggregate on-peak RTP ex ante load impacts for each monthly system peak day by weather year and forecast year. In accordance with the revised resource adequacy hours, the peak period is defined as 1 PM to 6 PM from April through October and 4 PM to 9 PM from November through March. Because RTP impacts are driven entirely by the daily price schedule, they depend highly on the previous day's temperature in downtown LA. In some cases, peak system conditions occur following a relatively cool day, as can be seen for July during a 1-in-10 weather year and June under 1-in-2 weather conditions. In particular, the system peak for June under 1-in-2 conditions occurs on a day with the mild summer weekday price schedule, so load impacts are negative.

Once enrollment steadies in August 2014, the program is expected to be capable of delivering 40.1 MW of load reduction on extremely hot summer weekdays, which occur during September under 1-in-2 system conditions and June, August and September in a 1-in-10 weather year (highlighted in the table). SCE system load typically peaks during August and September. For these monthly peaks in a 1-in-2 and 1-in-10 weather year, aggregate impacts are expected to double from 2011 to 2014 as a result of new enrollment.

Table 5-8:
RTP Aggregate On-Peak Load Impacts (MW)
for Each Monthly System Peak Day by Weather Year and Forecast Year
(Extremely Hot Summer Weekdays are Highlighted)

Weather Year	Month	Peak Period	2011	2012	2013	2014	2015-2021
1-in-2	Jan	4-9 PM	-0.6	-0.6	-1.0	-1.8	-2.3
	Feb	4-9 PM	-0.6	-0.6	-1.1	-1.9	-2.4
	Mar	4-9 PM	-0.9	-0.9	-1.4	-2.4	-2.8
	Apr	1-6 PM	-0.6	-0.6	-1.2	-2.1	-2.4
	May	1-6 PM	-0.6	-0.6	-1.3	-2.1	-2.4
	Jun	1-6 PM	-3.4	-3.4	-4.8	-6.5	-6.7
	Jul	1-6 PM	5.0	5.0	7.9	10.9	11.2
	Aug	1-6 PM	13.3	13.3	19.8	26.2	26.2
	Sep	**1-6 PM**	**19.5**	**20.4**	**30.7**	**40.1**	**40.1**
	Oct	1-6 PM	10.3	11.0	15.5	19.1	19.1
	Nov	4-9 PM	4.6	5.6	9.9	13.0	13.0
	Dec	4-9 PM	-0.5	-0.8	-1.6	-2.1	-2.1
1-in-10	Jan	4-9 PM	-0.6	-0.6	-0.9	-1.7	-2.2
	Feb	4-9 PM	-0.6	-0.6	-1.0	-1.8	-2.2
	Mar	4-9 PM	4.5	4.5	6.3	9.5	10.8
	Apr	1-6 PM	-0.5	-0.5	-0.9	-1.7	-1.9
	May	1-6 PM	8.6	8.6	11.9	16.2	17.3
	Jun	**1-6 PM**	**19.5**	**19.5**	**28.1**	**38.4**	**40.1**
	Jul	1-6 PM	5.0	5.0	7.9	10.9	11.2
	Aug	**1-6 PM**	**19.5**	**19.5**	**29.9**	**40.1**	**40.1**
	Sep	**1-6 PM**	**19.5**	**20.4**	**30.7**	**40.1**	**40.1**
	Oct	1-6 PM	10.3	11.0	15.5	19.1	19.1
	Nov	4-9 PM	-0.5	-0.7	-1.5	-2.0	-2.0
	Dec	4-9 PM	-0.6	-0.8	-1.6	-2.2	-2.2

Table 5-9 shows the aggregate on-peak RTP ex ante load impacts for each monthly average weekday by weather year and forecast year. As noted above, in accordance with the revised resource adequacy hours, the peak period is defined as 1 PM to 6 PM from April through October and 4 PM to 9 PM from November through March. The 1-in-2 load impacts do not vary substantially because the average hourly RTP price is not significantly different from the OAT for the average weekday in a normal weather year. From 2015 to 2021, the 1-in-2 aggregate impacts vary from around negative 2.7 MW in November through February to 7.7 MW in September. In a 1-in-10 weather year, average weekday aggregate impacts are as high as 12.3 MW in August.

Table 5-9:
RTP Aggregate On-Peak Load Impacts (MW)
for Each Monthly Average Weekday by Weather Year and Forecast Year

Weather Year	Month	Peak Period	2011	2012	2013	2014	2015-2021
1-in-2	Jan	4-9 PM	-0.8	-0.8	-1.2	-2.1	-2.6
	Feb	4-9 PM	-0.8	-0.8	-1.3	-2.2	-2.7
	Mar	4-9 PM	-0.5	-0.5	-1.0	-2.0	-2.3
	Apr	1-6 PM	-0.1	-0.1	-0.6	-1.4	-1.6
	May	1-6 PM	0.2	0.2	-0.2	-0.7	-0.8
	Jun	1-6 PM	-1.4	-1.4	-1.7	-2.1	-2.2
	Jul	1-6 PM	2.2	2.2	3.6	5.2	5.4
	Aug	1-6 PM	-0.5	-0.5	-0.5	-0.4	-0.4
	Sep	1-6 PM	3.5	3.7	5.8	7.7	7.7
	Oct	1-6 PM	1.4	1.4	1.9	2.3	2.3
	Nov	4-9 PM	-0.8	-1.1	-2.0	-2.7	-2.7
	Dec	4-9 PM	-0.8	-1.1	-2.1	-2.7	-2.7
1-in-10	Jan	4-9 PM	-0.7	-0.7	-1.1	-2.0	-2.6
	Feb	4-9 PM	-0.8	-0.8	-1.3	-2.3	-2.7
	Mar	4-9 PM	-0.6	-0.6	-1.0	-1.8	-2.1
	Apr	1-6 PM	-0.6	-0.6	-1.2	-2.1	-2.3
	May	1-6 PM	-0.7	-0.7	-1.4	-2.3	-2.6
	Jun	1-6 PM	1.6	1.6	2.6	3.8	4.0
	Jul	1-6 PM	0.7	0.7	1.4	2.2	2.2
	Aug	1-6 PM	5.6	5.6	9.0	12.3	12.3
	Sep	1-6 PM	5.1	5.3	8.2	10.8	10.8
	Oct	1-6 PM	3.2	3.5	4.7	5.8	5.8
	Nov	4-9 PM	-0.3	-0.3	-0.3	-0.3	-0.3
	Dec	4-9 PM	-0.7	-1.0	-2.0	-2.6	-2.6

5.5 RTP Recommendations

As discussed in Section 5.4, future aggregate load impacts are closely tied to the size of new participants relative to the existing population. If new participants are substantially smaller than the average existing RTP customer, the resulting aggregate load reduction will be relatively lower. On the other hand, if SCE is able to successfully market RTP and recruit more large customers over 25 MW, the resulting aggregate load reduction will be relatively higher. It is important that SCE continues to market RTP to large customers and not just focus on the smaller customers that the program will become available to in the near future.

As discussed in last year's evaluation, the program would also likely benefit from an analysis of how to further optimize price schedule selection. The schedules are currently selected based on downtown LA daily maximum temperatures on the previous day. The current rule is transparent and easy for participants to understand and track, but may not always target load impacts to time periods when they are most needed. Based on our extensive collective experience modeling system load and individual customer loads, the main difference between high and extreme system loads is not daily maximum temperature, but rather overnight heat build-up. We recommend assessing the incremental improvement of different pricing schedule selection rules and the associated tradeoffs, including the effect on transparency and clarity.