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2012 Load Impact Evaluation of Southern California Edison's Peak Time Rebate Program

CALMAC Study ID SCE0330

by

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EXECUTIVE SUMMARY

This report documents an impact evaluation of Southern California Edison's (SCE) Save Power Day (SPD) program for 2012. SPD is a peak time rebate (PTR) program in which customers are eligible to earn bill credits for usage reductions during event hours. In 2012, most SCE residential customers for whom SmartConnect meters had been installed and made operational were eligible for PTR. All PTR eligible customers who reduced energy usage relative to a customer-specific reference level (CRL) during events were eligible to receive bill credits regardless of whether they opted in, were defaulted to, or received no event notification. Customers were encouraged to sign up to receive electronic notification, or alerts, that an event was to take place.

This first-year evaluation of SPD (PTR) load impacts focuses on two broad categories of customers. One is the approximately 400,000 customers who were enrolled to receive electronic notification of events, either by "opting-in" to receive the notification, or by "default" in cases where SCE had information available on email addresses. The other category includes about 300,000 participants in SCE's Summer Discount Program (SDP) air conditioner cycling program, and whose SDP load impacts were estimated in an evaluation of that program.

The primary goals of this study are to estimate *ex post* and *ex ante* load impacts, or usage reductions, associated with the SPD (PTR) program in 2012.

Analysis Approach

The evaluation approach began with the design and selection of a sample of customers from the approximately 400,000 customers who were enrolled to receive electronic notification of PTR events as of the second event, on August 10. Hourly load data for the sampled customers, who were stratified by climate zone and size (usage level), were then aggregated into four groups defined by climate zone (Coastal and Inland) and type of notification (default and opt-in). Load-impact regression models were estimated for each group, after a process of testing and validating alternative models, including appropriate weather variables. In parallel, load data for all of the SDP participants were aggregated into three groups based on type of notification (default, opt-in, and no notice), and regression models were estimated for each group, producing estimates of hourly load impacts for each PTR event.

Key Study Findings

The key overall findings from the study are: 1) the non-SDP customers who opted to receive PTR event notifications were found to reduce usage during PTR event periods in statistically significant amounts of 0.07 kWh per hour, or 3.6 percent of their reference load, across the six PTR events included in the study, and 2) the SDP participants who opted-in to receive PTR event notification reduced usage by 0.20 kWh per hour, or 6.2 percent, also statistically significant. The estimated load impacts for the "default" notification groups of non-SDP and SDP customers were mixed, averaging non-statistically significant reductions of less than 1 percent, while the results for the no-notice portion of the SDP participants were even more mixed, averaging a non-significant 1 percent load increase.

In all, approximately 118,000 non-SDP customers and 28,000 SDP participants opted to receive notification, and they reduced load for the average PTR event by 14.1 MW. Adding in the relatively smaller estimated load reductions of the 285,000 non-SDP default customers and the 52,000 SDP default customers, the total PTR load reductions in 2012 amounted to 20.1 MWh per hour, averaged across the event hours of the six events included in the study.

Going forward, SCE anticipates relatively little growth in the number of customers who opt-in to receive event notification, but substantial growth in numbers of customers who are defaulted to receive notification. With that growth, ex ante load impacts are expected to average about 24 MW on an August peak event day in a 1-in-2 weather year in 2015.

1. INTRODUCTION AND KEY ISSUES

This report documents an impact evaluation of Southern California Edison's (SCE) Save Power Day (SPD) program for 2012. SPD is a peak time rebate (PTR) program in which customers are eligible to earn bill credits for usage reductions during event hours. In 2012, most SCE residential customers for whom SmartConnect meters had been installed and made operational were eligible for PTR. All PTR eligible customers who reduced energy usage relative to a customer-specific reference level (CRL) during events were eligible to receive bill credits regardless of whether they opted in, were defaulted to, or received no event notification. Customers were encouraged to sign up to receive electronic notification, or alerts, that an event was to take place.

SCE decided that the first-year evaluation of SPD load impacts would focus on two broad categories of customers. One was the approximately 400,000 customers who had enrolled to receive electronic notification of events, either by opting to receive the notification or by default in cases where SCE had information available on email addresses. The other category included about 300,000 customers who were also enrolled in SCE's Summer Discount Program (SDP) air conditioner cycling program and whose SDP load impacts were to be estimated in an evaluation of that program.

1.1 Project Goals

1. The primary goals of the project are to estimate *ex post* and *ex ante* load impacts, or usage reductions, associated with the PTR (SPD) program.
2. In the *ex ante* evaluation, estimate the following:
    - Program-level hourly load reductions on monthly system peak days and a typical event day, for 1-in-2 and 1-in-10 weather years;
    - Average participant's hourly load reductions for the same day types.

1.2 Roadmap to Report

Section 2 describes features of the PTR program. Section 3 discusses technical issues and the methodology used in conducting the study. Section 4 presents *ex post* load impact results. Section 5 describes the ex ante load impact results.

2. RESOURCES COVERED IN THE STUDY

This section begins by describing the features of the PTR program. It then lists the events that were called in 2012. Finally, it characterizes the nature of the participants in the various subgroups of interest.

2.1 Program Features

SCE's Save Power Day (PTR) program includes the following features:

- Two rebate levels are available—a basic level of $0.75/kWh and a premium level of $1.25/kWh for customers who use automated enabling technology installed through an SCE program.

- Load reductions for rebate purposes are measured relative to a customer-specific reference level (CRL) based on an average of the highest 3 out of the most recent 5 similar non-event days.[1]
- The number of events in a typical year may range from twelve to fifteen, usually during the summer, and always on weekdays, with an event window of 2 p.m. to 6 p.m. SCE called seven events in 2012 as the smart meters were still being deployed.

2.2 SPD (PTR) Events in 2012

Table 2–1 summarizes the seven PTR events that were called in 2012. The initial event on July 12 was not included in the ex post evaluation because a large number of customers were enrolled for notification between that event and the next one on August 10. Focusing on the last six events allowed consistency in enrollment across events.

Table 2–1: SPD (PTR) Event Days in 2012

Event Date	Day of Week	Average Event Temp.
07/12/2012	Thursday	85.2
08/10/2012	Friday	96.0
08/16/2012	Thursday	91.7
08/29/2012	Wednesday	91.8
08/31/2012	Friday	88.1
09/07/2012	Friday	86.9
09/10/2012	Monday	83.9

2.3 Participant Characteristics

2.3.1 Non-SDP Participants

This section provides information on the subset of the non-SDP population of SCE customers that had been enrolled to receive event notification prior to the August 10 event, and the samples of those customers that were drawn for this evaluation. Table 2–2 shows customer counts in the notified population and the selected sample in the two climate zones and three usage-level size groups. The sample design involved stratified random samples (by usage category) for the two climate zones, resulting in an overall sample of approximately 37,000 customers, and relatively higher sampling fractions in the high-usage categories.

[1] The "highest" days are those with the highest total consumption between the event window hours of 2 p.m. to 6 p.m.

Table 2–2: PTR Subgroup Populations and Sample Sizes

Climate Zone	Usage Category	Notified Population	Sample	Sample Fraction
Coastal	Low	96,436	5,522	5.7%
	Medium	122,160	8,932	7.3%
	High	33,490	5,533	16.5%
	Total	252,086	19,987	7.9%
Inland	Low	49,847	4,450	8.9%
	Medium	79,844	8,443	10.6%
	High	21,618	3,905	18.1%
	Total	151,309	16,798	11.1%

2.3.1 SDP Participants

Given the specific features of the SDP program, participating customers are characterized by their location, cycling strategy chosen, and air conditioner holdings. In SCE terminology, SDP customers reside within the territory of an A-bank, and each A-bank corresponds to one of six SCE geographic regions.[2] Table 2–3 summarizes characteristics of the residential SDP participants included in the PTR analysis. The first two columns indicate cycling strategy and region. The next four columns indicate the numbers of A-banks, participants (service accounts), the total number of their AC units, or devices, and the AC tons of those devices within each strategy/region. The last three columns characterize the AC tons and devices per service account (SAID). The AC information was not used in the evaluation of PTR load impacts.

Table 2–3: SDP Participants in 2012 and their Geographical Distribution

Cycling Strategy	Region	A-banks	Service Accounts	Devices	AC Tons	AC Tons / SAID	AC Tons / Device	Devices / SAID
100	SCEC	15	145,110	167,631	626,991	4.3	3.7	1.16
	SCEN	5	21,184	24,625	89,344	4.2	3.6	1.16
	SCEW	15	50,415	55,565	208,486	4.1	3.8	1.10
	SCHD	4	17,126	19,126	70,161	4.1	3.7	1.12
	SCLD	3	14,777	19,039	71,497	4.8	3.8	1.29
	SCNW	4	9,624	11,729	43,973	4.6	3.7	1.22
Total/Avg.		46	258,236	297,715	1,110,452	4.4	3.7	1.2
50	SCEC	15	13,660	14,914	54,887	4.0	3.7	1.09
	SCEN	5	1,556	1,723	6,035	3.9	3.5	1.11
	SCEW	15	5,918	6,325	23,133	3.9	3.7	1.07
	SCHD	3	843	900	3,237	3.8	3.6	1.07
	SCLD	2	1,596	1,907	7,194	4.5	3.8	1.19
	SCNW	3	915	1,060	4,018	4.4	3.8	1.16
Total/Avg.		43	24,488	26,829	98,504	4.1	3.7	1.1
Grand Total/Avg.		89	282,724	324,544	1,208,956	4.2	3.7	1.1

[2] A-banks are a geographic areas defined by group of distribution sub-stations. The six regions containing A-banks, also referred to as SLAPs, are defined as follows: SCEC=SCE Core (LA Basin), SCEN=SCE North, SCEW=SCE West, SCHD= SCE High Desert, SCLD=SCE Low Desert, and SCNW=SCE Northwest.

3. ANALYSIS METHODS

This section discusses technical issues to be addressed in this study, including sample design, methods for estimating ex post load impacts, and development of the *ex ante* forecasts. Sample design was based on customer and usage data provided by SCE, and was guided by targeted levels of precision in estimating load impacts. Our approach for conducting the *ex post* impact evaluation involves exploration and testing of traditional regression-based methods for estimating load impacts for event-based demand response programs. These methods apply regression analysis to hourly load data for subgroups and samples of participating customers, using customers' own loads on non-event days as controls for their use on event days (i.e., *"participant-only"* approach). The analysis controls for factors other than PTR events that influence customers' load profiles, including hour of day, day of week, and weather conditions, and also includes hourly variables that indicate event days. The coefficients on the event variables allow direct estimation of hourly PTR load impacts for each event day.

3.1 Sample Design

The key factors that guided the sample design were the number of characteristics by which the sample should be stratified (e.g., climate zone and customer size), and the required sample sizes. Sample size requirements are generally related to two primary factors: 1) the variability in usage across customers, and 2) the expected size of the event-day usage reductions that need to be estimated. CA Energy Consulting worked closely with SCE staff on the sample design and selection of customers. We obtained customer counts by usage bin and established stratum boundary points using Dalenius-Hodges techniques. Sample sizes were determined by criteria of 90/10 precision for relatively small anticipated PTR load impacts. This resulted in relatively large sample sizes, which were allocated to strata using Neyman allocations. SCE then selected customers at random according to the design parameters (i.e., sample sizes and sample strata).

3.2 Level of Analysis

Our evaluation of the non-SDP portion of customers was undertaken at an aggregate group level, in which the hourly loads for all sample customers in a given climate zone and type of notice (default or opt-in) were added together (using appropriate sample weights to collapse across usage categories), and regression analysis was applied to hourly data for the four groups for the period of July 15 through September 14, 2012. Data for the period prior to July 15, which included the first PTR event, were excluded because a large portion of the customers were enrolled between the first and second event, so this approach included as many customers as possible without having to control for enrollment dates.

An analogous approach was used for the evaluation of PTR load impacts for SDP customers. In that case, customers' loads were aggregated into three notification-based groups: default, opt-in, and non-notified. In all cases, weather variables were constructed as appropriate averages across customers in the groups.

3.3 Estimating *Ex Post* Load Impacts

The model presented below represents the "base" *ex post* load impact model that was used to estimate hourly impacts for each event day, for the individual customer accounts, while controlling for factors such as weather conditions and regular daily and monthly usage patterns (*i.e.*, accounting for differences in load levels across hours of the day, days of the week, and months of the year). The base model is:

$$
\begin{aligned}
Q_t = {} & \alpha + \sum_{Evt=1}^{E}\sum_{i=1}^{24}(\beta_i^{Evt} \times h_{i,t} \times DR_t) + \sum_{i=1}^{24}(\beta_i^{Wth} \times h_{i,t} \times Wth_t) + \sum_{i=1}^{24}\beta_i^{MornLoad} \times MornLoad_t \\
& + \sum_{i=1}^{5}\sum_{j=1}^{24}(\beta_{i,j}^{DT,H} \times DT_{i,t} \times h_{j,t}) + \sum_{i=8}^{9}(\beta_i^{MONTH} \times MONTH_{i,t}) + \sum_{i=2}^{24}(\beta_i^{Sep} \times SEP_{i,t} \times h_{i,t}) \\
& + \sum_{i=2}^{24}(\beta_i^{Conserve} \times Conserve_t \times h_{i,t}) + \sum_{i=2}^{24}(\beta_i^{Fkex} \times Flex_t \times h_{i,t}) + e_t
\end{aligned}
$$

The variables are explained in the table below.

Variable Name / Term	Variable / Term Description
Q_t	the customer's demand in hour *t*
α and the various β's	the estimated parameters
$h_{i,t}$	a dummy variable for hour *i*
DR_t	an indicator variable for program event days
Wth_t	weather conditions during hour *t* (e.g., measured by CDD, CDH, or THI)
E	the number of event days that occurred during the program year
$MornLoad_t$	a variable equal to the average of the day's load in hours 1 through 10
$DT_{i,t}$	a dummy variable for day type *i*
$MONTH_{i,t}$	a series of dummy variables for each month
$SEP_{i,t}$	a dummy variable for the month of September
$Conserve_t$	a dummy variable for days on which CAISO encouraged conservation (near Flex Alert days)
$Flex_t$	a dummy variable for CAISO Flex Alert days
e_t	the error term.

The first term in the equation that contains the double summation signs is the component of the equation that allows estimation of *hourly load impacts* (the b^{Evt}_i coefficients). It does so via the hourly indicator variables $h_{i,t}$ interacted with the event variables (indicated by DR_t). The remaining terms in the equation are designed to control for weather and other periodic factors (e.g., hours, days, and months) that determine customers' loads. The interaction of day-type indicators with the hourly indicators is designed to account for potentially different hourly load profiles on different days of the workweek and weekends.

We allow for a different hourly profile during the month of September to account for changes in usage patterns that may occur when summer ends and children return to school. The "morning load" variable is used in the same spirit as the optional day-of adjustment to the 10-in-10 baseline method currently used in some DR programs (e.g., Demand Bidding Program). That is, it is intended to adjust the reference load (i.e., the regression-based estimate of the loads that are expected to occur on a given day, including the load that would have occurred on event days if the events had not been called) for unobservable exogenous factors that cause loads to vary from day to day.[3]

We tested a variety of specifications to determine the regression model that performs best according to several performance and validity tests. The tests and their results are described in detail in Appendix A.

3.4 Estimating *Ex Ante* Load Impacts

Estimating *ex ante* load impacts for future years requires three key pieces of information:

- An *enrollment forecast* for the program, which for PTR consists of a forecast of residential customers who are enrolled to receive electronic event notification
- *Reference loads* by customer type;
- A forecast of *load impacts per customer*, again by relevant customer type, where the load impact forecast also varies with weather conditions, as determined in the *ex post* evaluation.

SCE provided the first item, the enrollment forecasts. The second item, per-customer reference loads, by the customer types listed above, are based on simulations from regression models similar to those used in the *ex post* load impact analyses for the summer period (modified as needed for use in the ex ante context), and from separate regressions estimated using data for non-summer months. Reference loads are then simulated using the appropriate weather data (i.e., the 1-in-2 and 1-in-10 weather-year scenarios) and event-day characteristics. The third element, load impacts per customer, are derived from the *ex post* load impact estimates.

4. STUDY FINDINGS—EX POST LOAD IMPACTS

This section reports estimated load impacts for each PTR event, for various customer groups and in total.

4.1 Summary Load Impacts

This section provides summary tables of average hourly estimated reference loads and load impacts for each event, at an average-customer and aggregate level, for various groups of customers. Results for non-SDP customers are shown first, followed by those for SDP customers.

[3] The use of the morning load variable assumes that variations in the morning load are related to variations in reference loads later in the day; but that the changes in the morning load are not part of the customer's response to the event itself (e.g., pre-cooling). If customers do shift usage to morning hours, the presence of the morning variable could produce an upward bias in the load impact estimate. (That is, the reference load will be shifted too high under the assumption that exogenous factors have increased the customer's reference load.) In our experience, there does not appear to be a significant amount of pre-cooling or other load shifting behavior, at least into hours 1 through 10 on event days, and the presence of the morning load variable has helped to estimate more reasonable load impacts in some difficult cases of highly variable loads. We will continue to examine event-day behavior for the 2012 program year to ensure that this remains the case, and remove the variable if we determine that it is not improving the load impact estimates.

4.1.1 Non-SDP Customers

Table 4–1 shows average hourly estimated reference loads and load impacts for each event for non-SDP participants, by climate zone and type of notification. Results are shown for the average customer and in total, where the aggregate results are obtained by scaling up using appropriate sample scaling factors. Tables 4–2 and 4–3 show similar information for the two geographical areas of Southern Orange County and South of Lugo respectively.

The load impact estimates are mixed, and vary considerably across events and customer groups. The Inland Opt-in group shows the most consistent and statistically significant usage reductions, generally ranging from 0.02 to 0.32 kWh/hour, or from 1 to 10 percent of reference usage levels, and averaging 4 percent. The Coastal Opt-in group has similar results for the first four events. However, the last two events are characterized by usage increases. The results for the Default groups in both climate zones are more mixed, with as many estimated usage increases and reductions, nearly all of which are not statistically significant.

Tables 4–2 and 4–3 show comparable information for two subsets of customers for whom SCE has been requested to report results – customers who reside in Southern Orange County, and customers located in an area known as South of Lugo.

Table 4–1: Residential SPD (PTR) Average Hourly Load Impacts – *Non-SDP Participants*

				Average Customer		Aggregate			
Event Date	Region	Notice	Number of Accounts	Reference Load (kW)	Load Impact (kW)	Reference Load (MW)	Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	Coastal	Opt-in	46,092	1.4	0.100	66.4	4.6	6.9%	86.7
08/16/2012			46,079	1.2	0.089	56.7	4.1	7.2%	82.1
08/29/2012			46,079	1.3	0.017	61.8	0.8	1.3%	81.9
08/31/2012			46,079	1.3	0.059	58.7	2.7	4.6%	81.4
09/07/2012			46,073	1.1	-0.037	52.4	-1.7	-3.2%	82.0
09/10/2012			46,073	1.3	-0.027	59.5	-1.2	-2.1%	82.3
Average	**Coastal**	**Opt-in**	**46,079**	**1.3**	**0.034**	**59.2**	**1.5**	**2.6%**	**82.7**
08/10/2012	Coastal	Default	205,562	1.7	0.085	354.4	17.6	5.0%	86.4
08/16/2012			205,562	1.4	0.080	296.6	16.4	5.5%	81.9
08/29/2012			205,527	1.6	-0.017	325.4	-3.5	-1.1%	82.2
08/31/2012			205,521	1.5	-0.026	300.7	-5.3	-1.8%	81.1
09/07/2012			205,555	1.3	-0.095	270.8	-19.5	-7.2%	81.6
09/10/2012			205,526	1.5	-0.038	316.7	-7.8	-2.5%	82.5
Average	**Coastal**	**Default**	**205,542**	**1.5**	**-0.002**	**310.8**	**-0.3**	**-0.1%**	**82.6**
08/10/2012	Inland	Opt-in	71,897	3.2	0.322	226.6	23.1	10.2%	99.6
08/16/2012			71,880	2.6	0.031	184.2	2.2	1.2%	95.7
08/29/2012			71,874	2.7	0.189	196.3	13.6	6.9%	97.0
08/31/2012			71,865	2.2	0.002	158.2	0.1	0.1%	92.2
09/07/2012			71,823	2.1	0.024	150.7	1.7	1.1%	90.0
09/10/2012			71,837	2.2	0.022	155.5	1.6	1.0%	86.6
Average	**Inland**	**Opt-in**	**71,863**	**2.5**	**0.098**	**178.6**	**7.1**	**4.0%**	**93.5**
08/10/2012	Inland	Default	79,121	3.6	0.355	287.9	28.1	9.7%	101.6
08/16/2012			79,140	3.0	-0.026	234.0	-2.1	-0.9%	97.3
08/29/2012			79,120	3.0	0.043	236.7	3.4	1.5%	96.7
08/31/2012			79,105	2.5	-0.023	195.8	-1.8	-0.9%	92.3
09/07/2012			79,124	2.4	0.058	191.0	4.6	2.4%	89.7
09/10/2012			79,115	2.3	-0.034	185.6	-2.7	-1.4%	83.2
Average	**Inland**	**Default**	**79,121**	**2.8**	**0.062**	**221.8**	**4.9**	**2.2%**	**93.5**
08/10/2012	All	Default	284,683	2.3	0.160	642.3	45.6	7.1%	93.2
08/16/2012			284,701	1.9	0.050	530.6	14.4	2.7%	88.7
08/29/2012			284,647	2.0	0.000	562.1	-0.1	0.0%	88.3
08/31/2012			284,626	1.7	-0.025	496.5	-7.1	-1.4%	85.5
09/07/2012			284,679	1.6	-0.052	461.8	-14.9	-3.2%	85.0
09/10/2012			284,641	1.8	-0.037	502.3	-10.5	-2.1%	82.8
Average	**All**	**Default**	**284,663**	**1.9**	**0.016**	**532.6**	**4.6**	**0.9%**	**87.2**
08/10/2012	All	Opt-in	117,990	2.5	0.235	292.9	27.8	9.5%	96.7
08/16/2012			117,958	2.0	0.053	240.9	6.3	2.6%	92.5
08/29/2012			117,953	2.2	0.122	258.1	14.4	5.6%	93.4
08/31/2012			117,943	1.8	0.024	216.9	2.8	1.3%	89.3
09/07/2012			117,896	1.7	0.000	203.1	0.0	0.0%	87.9
09/10/2012			117,909	1.8	0.003	215.1	0.4	0.2%	85.4
Average	**All**	**Opt-in**	**117,942**	**2.0**	**0.073**	**237.8**	**8.6**	**3.6%**	**90.9**
08/10/2012	All	All	402,673	2.3	0.182	935.2	73.4	7.8%	94.3
08/16/2012			402,660	1.9	0.051	771.5	20.7	2.7%	89.9
08/29/2012			402,600	2.0	0.036	820.2	14.3	1.7%	89.9
08/31/2012			402,570	1.8	-0.011	713.3	-4.3	-0.6%	86.7
09/07/2012			402,574	1.7	-0.037	664.9	-14.8	-2.2%	85.9
09/10/2012			402,551	1.8	-0.025	717.4	-10.1	-1.4%	83.6
Average	**All**	**All**	**402,604**	**1.9**	**0.033**	**770.4**	**13.2**	**1.7%**	**88.4**

Table 4–2: Residential SPD (PTR) Average Hourly Load Impacts –
Non-SDP Participants, in Southern Orange County

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South Orange County	All	111,786	1.5	0.058	169.8	6.5	3.8%	85.4
08/16/2012			111,792	1.3	0.074	145.2	8.3	5.7%	81.1
08/29/2012			111,772	1.4	-0.015	157.0	-1.7	-1.1%	81.8
08/31/2012			111,780	1.3	-0.052	143.6	-5.8	-4.0%	80.3
09/07/2012			111,786	1.2	-0.089	129.4	-10.0	-7.7%	80.7
09/10/2012			111,757	1.4	-0.042	153.2	-4.7	-3.1%	82.2
Average	**South Orange County**	**All**	**111,779**	**1.3**	**-0.011**	**149.7**	**-1.2**	**-0.8%**	**81.9**

Table 4–3: Residential SPD (PTR) Average Hourly Load Impacts –
Non-SDP Participants, South of Lugo

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South of Lugo, Coastal	All	85,970	2.2	0.198	185.2	17.0	9.2%	87.7
08/16/2012			85,964	1.8	0.194	155.2	16.7	10.8%	82.8
08/29/2012			85,964	2.0	0.005	168.0	0.4	0.2%	83.8
08/31/2012			85,950	1.8	0.000	151.7	0.0	0.0%	81.9
09/07/2012			85,978	1.6	-0.106	136.9	-9.1	-6.7%	82.5
09/10/2012			85,978	1.8	-0.046	158.7	-4.0	-2.5%	84.0
Average	**Coastal**	**All**	**87,954**	**1.8**	**0.040**	**159.3**	**3.5**	**2.2%**	**83.8**
08/10/2012	South of Lugo, Inland	All	72,784	3.3	0.191	243.8	13.9	5.7%	101.4
08/16/2012			72,794	3.0	0.092	216.8	6.7	3.1%	98.6
08/29/2012			72,797	3.1	0.179	227.9	13.1	5.7%	98.1
08/31/2012			72,797	2.4	-0.108	175.3	-7.8	-4.5%	92.8
09/07/2012			72,765	2.2	-0.043	161.1	-3.1	-1.9%	89.3
09/10/2012			72,788	2.4	-0.081	177.5	-5.9	-3.3%	86.1
Average	**Inland**	**All**	**129,186**	**1.6**	**0.022**	**200.4**	**2.8**	**1.4%**	**94.4**
08/10/2012	South of Lugo	All	158,755	2.7	0.195	429.0	30.9	7.2%	95.5
08/16/2012			158,758	2.3	0.147	372.0	23.4	6.3%	92.0
08/29/2012			158,761	2.5	0.085	395.9	13.5	3.4%	92.0
08/31/2012			158,747	2.1	-0.049	327.0	-7.8	-2.4%	87.7
09/07/2012			158,742	1.9	-0.077	298.0	-12.2	-4.1%	86.2
09/10/2012			158,766	2.1	-0.062	336.2	-9.9	-2.9%	85.1
Average	**South of Lugo**	**All**	**158,755**	**2.3**	**0.040**	**359.7**	**6.3**	**1.8%**	**89.8**

4.1.2 SDP Customers

Tables 4–4 through 4–8 contain similar information for PTR customers who were also enrolled in SDP. In this case, results are shown for customers who were not enrolled to receive event notification, as well as those enrolled for Default and Opt-in notification. For comparability with the non-SDP results, the last panel in Table 4–4 shows total results for the combination of Default and Opt-in customers. That breakdown is provided for the Southern Orange County and South of Lugo categories in Tables 4–6 and 4–8.

Similarly to the non-SDP customers, the subset of PTR opt-in customers among the SDP participants provided the most consistent and statistically significant load reductions on PTR event days. Estimated load reductions averaged nearly 0.20 kWh per hour, or 6.2 percent of the reference load (note that the SDP participants are typically substantially larger than the non-SDP customers). Usage reductions were estimated for four of six events for the customers with default notification, but the average load impact was less than 1 percent and not statistically significant. The largest, no-notice group produced a mix of estimated load reductions and increases, with an average increase of less than 1 percent, and again not statistically significant.

Table 4–4: Residential PTR Average Hourly Load Impacts – *SDP Participants*

				Average Customer		Aggregate			
Event Date	Region	Notice	Number of Accounts	Reference Load (kW)	Load Impact (kW)	Reference Load (MW)	Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	All	Opt-in	28,138	4.1	0.421	114.3	11.9	10.4%	96.0
08/16/2012			28,120	3.3	0.174	93.6	4.9	5.2%	91.7
08/29/2012			28,106	3.3	0.243	91.4	6.8	7.5%	91.8
08/31/2012			28,100	2.9	0.126	81.6	3.5	4.3%	88.1
09/07/2012			28,100	2.6	0.004	73.6	0.1	0.2%	86.9
09/10/2012			28,099	2.7	0.201	77.1	5.7	7.3%	83.9
Average	**All**	**Opt-in**	**28,111**	**3.2**	**0.195**	**88.6**	**5.5**	**6.2%**	**89.7**
08/10/2012	All	Default	51,648	4.3	0.206	223.4	10.6	4.8%	96.0
08/16/2012			51,627	3.7	-0.022	188.9	-1.1	-0.6%	91.7
08/29/2012			51,609	3.5	0.015	180.4	0.8	0.4%	91.8
08/31/2012			51,606	3.2	0.015	164.4	0.8	0.5%	88.1
09/07/2012			51,597	2.8	-0.163	144.8	-8.4	-5.8%	86.9
09/10/2012			51,597	3.0	0.118	156.0	6.1	3.9%	83.9
Average	**All**	**Default**	**51,614**	**3.4**	**0.028**	**176.3**	**1.5**	**0.8%**	**89.7**
08/10/2012	All	No Notice	193,156	4.0	0.079	767.3	15.3	2.0%	96.0
08/16/2012			193,881	3.3	0.001	643.9	0.2	0.0%	91.7
08/29/2012			195,453	3.2	-0.035	635.0	-6.8	-1.1%	91.8
08/31/2012			195,654	2.8	-0.041	556.1	-8.0	-1.4%	88.1
09/07/2012			195,850	2.6	-0.184	514.0	-36.1	-7.0%	86.9
09/10/2012			195,882	2.8	0.022	547.1	4.4	0.8%	83.9
Average	**All**	**No Notice**	**194,979**	**3.1**	**-0.027**	**610.6**	**-5.2**	**-0.8%**	**89.7**
08/10/2012	All	All	272,942	4.0	0.138	1,104.9	37.8	3.4%	96.0
08/16/2012			273,628	3.4	0.015	926.3	4.0	0.4%	91.7
08/29/2012			275,168	3.3	0.003	906.9	0.8	0.1%	91.8
08/31/2012			275,360	2.9	-0.013	802.1	-3.7	-0.5%	88.1
09/07/2012			275,547	2.7	-0.161	732.5	-44.4	-6.1%	86.9
09/10/2012			275,578	2.8	0.058	780.2	16.1	2.1%	83.9
Average	**All**	**All**	**274,704**	**3.2**	**0.006**	**875.5**	**1.8**	**0.2%**	**89.7**
08/10/2012	All	Opt-in & Default Only	79,786	4.2	0.282	337.7	22.5	6.7%	96.0
08/16/2012			79,747	3.5	0.047	282.5	3.8	1.3%	91.7
08/29/2012			79,715	3.4	0.095	271.9	7.6	2.8%	91.8
08/31/2012			79,706	3.1	0.054	246.0	4.3	1.7%	88.1
09/07/2012			79,697	2.7	-0.104	218.5	-8.3	-3.8%	86.9
09/10/2012			79,696	2.9	0.147	233.1	11.7	5.0%	83.9
Average	**All**	**Notified**	**79,725**	**3.3**	**0.087**	**264.9**	**6.9**	**2.6%**	**89.7**

Table 4–5: Residential PTR Average Hourly Load Impacts –
SDP Participants in Southern Orange County

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South Orange County	All	20,904	4.1	0.178	85.6	3.7	4.4%	85.4
08/16/2012			20,940	3.4	0.025	71.7	0.5	0.7%	81.1
08/29/2012			21,025	3.3	0.029	69.9	0.6	0.9%	81.8
08/31/2012			21,035	3.0	0.005	62.2	0.1	0.2%	80.3
09/07/2012			21,045	2.7	-0.144	56.4	-3.0	-5.4%	80.7
09/10/2012			21,047	2.9	0.083	60.1	1.7	2.9%	82.2
Average	**South Orange County**	**All**	**20,999**	**3.2**	**0.029**	**67.6**	**0.6**	**0.9%**	**81.9**

Table 4–6: Residential PTR Average Hourly Load Impacts –
SDP Participants in Southern Orange County (PTR Notified)

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South Orange County	Opt-in & Default Only	10,019	4.2	0.286	42.3	2.9	6.8%	85.4
08/16/2012			10,014	3.5	0.051	35.4	0.5	1.4%	81.1
08/29/2012			10,010	3.4	0.100	34.1	1.0	2.9%	81.8
08/31/2012			10,009	3.1	0.056	30.8	0.6	1.8%	80.3
09/07/2012			10,008	2.7	-0.100	27.4	-1.0	-3.7%	80.7
09/10/2012			10,008	2.9	0.149	29.2	1.5	5.1%	82.2
Average	**South Orange County**	**All**	**10,011**	**3.3**	**0.090**	**33.2**	**0.9**	**2.7%**	**81.9**

Table 4–7: Residential PTR Average Hourly Load Impacts –
SDP Participants South of Lugo

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South of Lugo	All	102,156	4.1	0.149	415.5	15.2	3.7%	97.2
08/16/2012			102,386	3.4	0.016	348.4	1.6	0.5%	93.9
08/29/2012			102,907	3.3	0.009	340.5	0.9	0.3%	93.8
08/31/2012			102,972	2.9	-0.009	301.8	-0.9	-0.3%	89.1
09/07/2012			103,034	2.7	-0.158	274.8	-16.3	-5.9%	87.0
09/10/2012			103,045	2.8	0.065	292.9	6.7	2.3%	85.4
Average	**South of Lugo**	**All**	**102,750**	**3.2**	**0.012**	**329.0**	**1.2**	**0.4%**	**91.1**

Table 4–8: Residential PTR Average Hourly Load Impacts – *SDP Participants South of Lugo (PTR Notified)*

Event Date	Region	Notice	Number of Accounts	Average Customer Reference Load (kW)	Average Customer Load Impact (kW)	Aggregate Reference Load (MW)	Aggregate Load Impact (MW)	% Load Impact	Average Event Temp.
08/10/2012	South of Lugo	Opt-in & Default Only	36,293	4.2	0.276	153.9	10.0	6.5%	97.2
08/16/2012			36,276	3.6	0.042	128.8	1.5	1.2%	93.9
08/29/2012			36,261	3.4	0.089	123.9	3.2	2.6%	93.8
08/31/2012			36,258	3.1	0.051	112.2	1.8	1.6%	89.1
09/07/2012			36,253	2.7	-0.109	99.6	-3.9	-4.0%	87.0
09/10/2012			36,253	2.9	0.145	106.3	5.2	4.9%	85.4
Average	**South of Lugo**	**All**	**36,266**	**3.3**	**0.082**	**120.8**	**3.0**	**2.5%**	**91.1**

4.2 Hourly Program Load Impacts

Figures 4–1 and 4–2 show the hourly profiles of the estimated reference loads, observed loads and estimated load impacts (right axis) for the two groups of opt-in notification customers from the non-SDP customers and the SDP participants respectively, both of which produced statistically significant estimated load reductions.

Figure 4–1: Hourly Estimated Reference Load, Observed Load, and Estimated Load Impacts – *Opt-in Notification; non-SDP; Average Event*

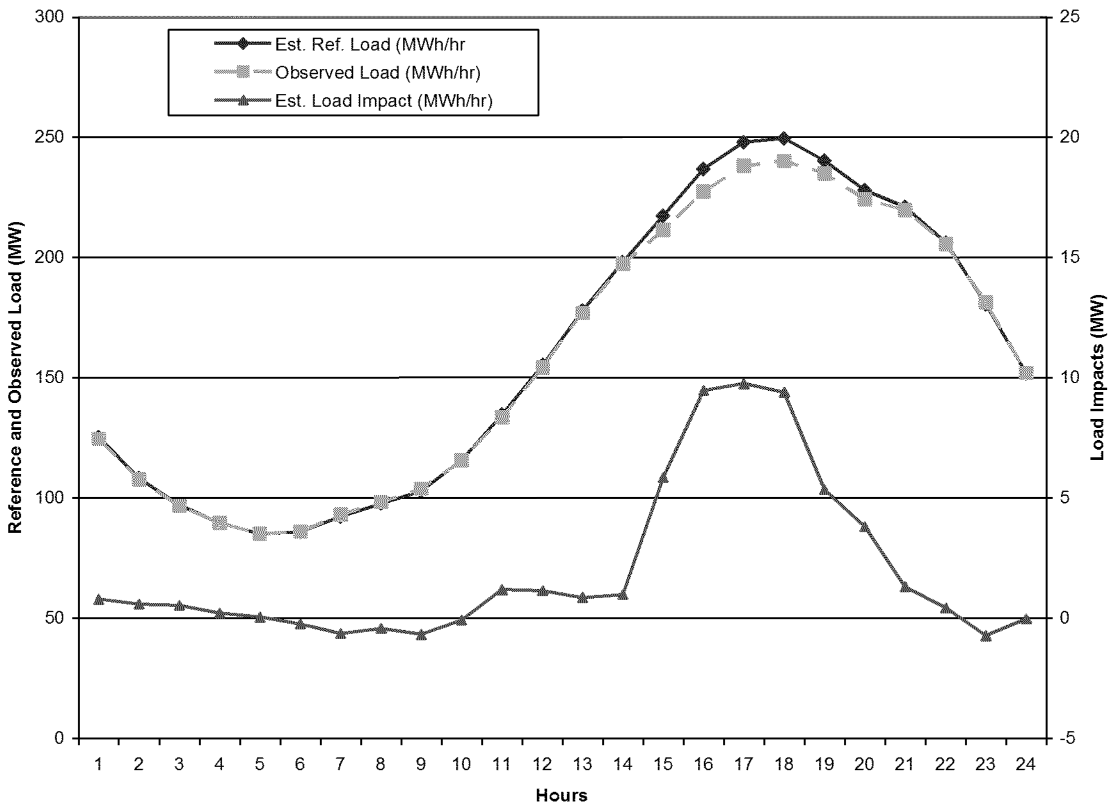
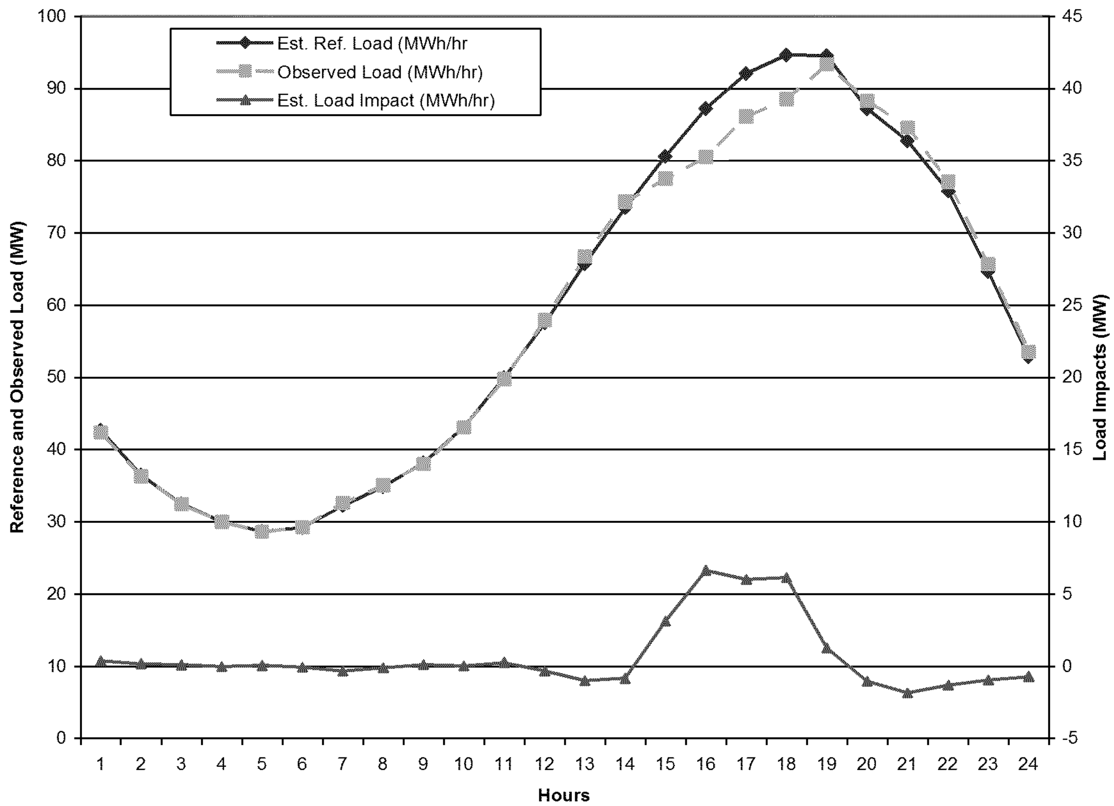


Figure 4–2: Hourly Estimated Reference Load, Observed Load, and Estimated Load Impacts – *Opt-in Notification; SDP Customers; Average Event*



5. EX ANTE EVALUATION

5.1 Ex Ante Load Impact Requirements

The DR Load Impact Evaluation Protocols require that hourly load impact forecasts for event-based DR resources must be reported at the program level and by LCA for the following scenarios:

- For a typical event day in each year; and
- For the monthly system peak load day in each month for which the resource is available;

under both:

- 1-in-2 weather-year conditions, and
- 1-in-10 weather-year conditions.

at both:

- the program level (i.e., in which only the program in question is called), and
- the portfolio level (i.e., in which all demand response programs are called).

5.2 Description of Methods

This section describes the methods used to develop the relevant groups of customers, to develop reference loads for the relevant customer types and event day-types, and to develop percentage load impacts for a typical event day.

5.2.1 Development of Customer Groups

The ex ante forecast includes only notified customers, which are divided into groups according to several criteria:

- Whether the customer opted into or was defaulted onto event notification;
- LCA; and
- Dual enrollment with SDP.

5.2.2 Development of Reference Loads and Load Impacts

Reference loads and load impacts for all of the above customer groups and scenarios were developed in the following series of steps:

1. Define data sources;
2. Estimate ex ante regressions and simulate reference loads by customer and scenario;
3. Calculate percentage load impacts from ex post results;
4. Apply percentage load impacts to the reference loads; and
5. Scale the reference loads using enrollment forecasts.

Each of these steps is described below.

Define data sources. The reference loads and percentage load impacts are developed using data for the sample of notified customers used in the ex post analysis. We did not have non-summer load data for the customers dually enrolled in SDP and PTR, so we used the summer data to find the PTR customers that most closely approximated the SDP customers and used those data to forecast SDP non-summer reference loads. The load profile was a weighted average of the medium (80 percent) and high-use (20 percent) customers in the Inland region.

Simulate reference loads. In order to develop reference loads, we first re-estimated regression equations for each customer group using data for the current program year. The resulting estimates were used to simulate reference loads for each group under the various scenarios required by the Protocols (e.g., the typical event day in a 1-in-2 weather year).

For the summer months, the re-estimated regression equations were similar in design to the ex post load impact equations described in Section 3.3, differing in two ways. First, the ex ante models excluded the morning-usage variables. While these variables are useful for improving accuracy in estimating ex post load impacts for particular events, they complicate the use of the equations in ex ante simulation. That is, they would require a separate simulation of the level of the morning load. The second difference between the ex post and ex ante models is that the ex ante models use CDH60 as the weather variables in place of the weather variables used in the ex post regressions. The primary reason for this is that ex ante weather days were selected based on current-day temperatures, not factoring in lagged values or humidity. Therefore, we determined that this method is the most consistent way of reflecting the 1-in-2 and 1-in-10 weather conditions.

Because PTR events may be called in any month of the year, we estimated separate regression models to allow us to simulate non-summer reference loads. The non-summer model is shown below. This model is estimated separately from the summer ex ante model. It only differs from the summer model in three ways: it includes HDH_t variables, where the summer model does not; the month dummies relate to a different set of months; and the event variables are removed (because no event days occurred during the regression timeframe). Table 5–1 describes the terms included in the equation.

$$
\begin{aligned}
Q_t = a &+ \sum_{i=1}^{24}(b_i^{CDH} \times h_{i,t} \times CDH_t) + \sum_{i=1}^{24}(b_i^{HDH} \times h_{i,t} \times HDH_t) + \sum_{i=2}^{24}(b_i^{MON} \times h_{i,t} \times MON_t) \\
&+ \sum_{i=2}^{24}(b_i^{FRI} \times h_{i,t} \times FRI_t) + \sum_{i=2}^{24}(b_i^{h} \times h_{i,t}) + \sum_{i=2}^{5}(b_i^{DTYPE} \times DTYPE_{i,t}) \\
&+ \sum_{i=2..5,10..12}(b_i^{MONTH} \times MONTH_{i,t}) + e_t
\end{aligned}
$$

Table 5–1: Descriptions of Terms included in the Ex Ante Regression Equation

Variable Name	Variable Description
Q_t	the demand in hour *t* for the modeled customer group
The various *b*'s	the estimated parameters
$h_{i,t}$	a dummy variable for hour *i*
CDH_t	cooling degree hours
HDH_t	heating degree hours[4]
MON_t	a dummy variable for Monday
FRI_t	a dummy variable for Friday
$DTYPE_{i,t}$	a series of dummy variables for each day of the week
$MONTH_{i,t}$	a series of dummy variables for each month
e_t	the error term.

Once these models were estimated, we simulated 24-hour load profiles for each required scenario. The typical event day was assumed to occur in August. Much of the differences across scenarios can be attributed to varying weather conditions. The definitions of the 1-in-2 and 1-in-10 weather years were provided by SCE.

[4] Heating degree hours (HDH) was defined as MAX[0, 50 – TMP], where TMP is the hourly temperature expressed in degrees Fahrenheit. Customer-group-specific HDH values are calculated using data from the most appropriate weather station.

Calculate forecast percentage load impacts. The percentage load impacts were based upon the ex post load impacts. Because there was no clear pattern of pre- or post-event hour load impacts, we examined only event-hour load impacts. Our starting point for the percentage load impacts is to calculate the average and standard deviation of the event-hour percentage load impacts across the observed event days. For the PTR-only default notice customers, these values are 0.86 percent and 3.85 percent, respectively. For the PTR-only opt-in notice customers, they are 3.62 percent and 3.71 percent.

In order to adjust these values for differences between ex post and ex ante weather conditions, we varied the ex post hourly percentage load impact using the estimated elasticity of substitution equations from the Statewide Pricing Pilot (SPP).[5] In those equations, the elasticity of substitution varies with the weather conditions (the difference between peak and off-peak cooling degree hours), the central air conditioning saturation rate, and season (summer, winter, and "inner" winter).

Using these SPP equations, we simulated the elasticity of substitution for the typical ex post event day and then performed the same calculation for each of the Protocol scenarios. The hourly percentage load impacts for each Protocol scenario were then calculated as the average ex post percentage load impact multiplied by the ratio of the SPP elasticity of substitution for the Protocol day divided by the value for the typical ex post event day.

The uncertainty-adjusted scenarios of load impacts were developed by applying the standard deviation of the ex post percentage load impacts (calculated across ex post event days) to the forecast reference load. The percentage load impacts for each of the 10th, 30th, 50th, 70th, and 90th scenarios were generated under the assumption that the percentage load impact is normally distributed with a mean equal to the SPP-adjusted percentage load impact described above and the standard deviation calculated from the ex post event days.

Apply percentage load impacts to reference loads for each event scenario. In this step, the percentage load impacts were applied to the reference loads for each scenario to produce all of the required reference loads, estimated event-day loads, and scenarios of load impacts. In each case, the percentage load impact is applied to the event windows required by the Protocols, which are 1:00 to 6:00 p.m. from April through October and 4:00 to 9:00 p.m. in all other months.

Apply forecast enrollments to produce program-level load impacts. SCE provided enrollment forecasts separately for opt-in and default notice customer. We used information from PY2012 (or current data, if available) to divide these customers into LCAs and to determine the share of customers that are dually enrolled in SDP and PTR. The enrollments are monthly through 2015,

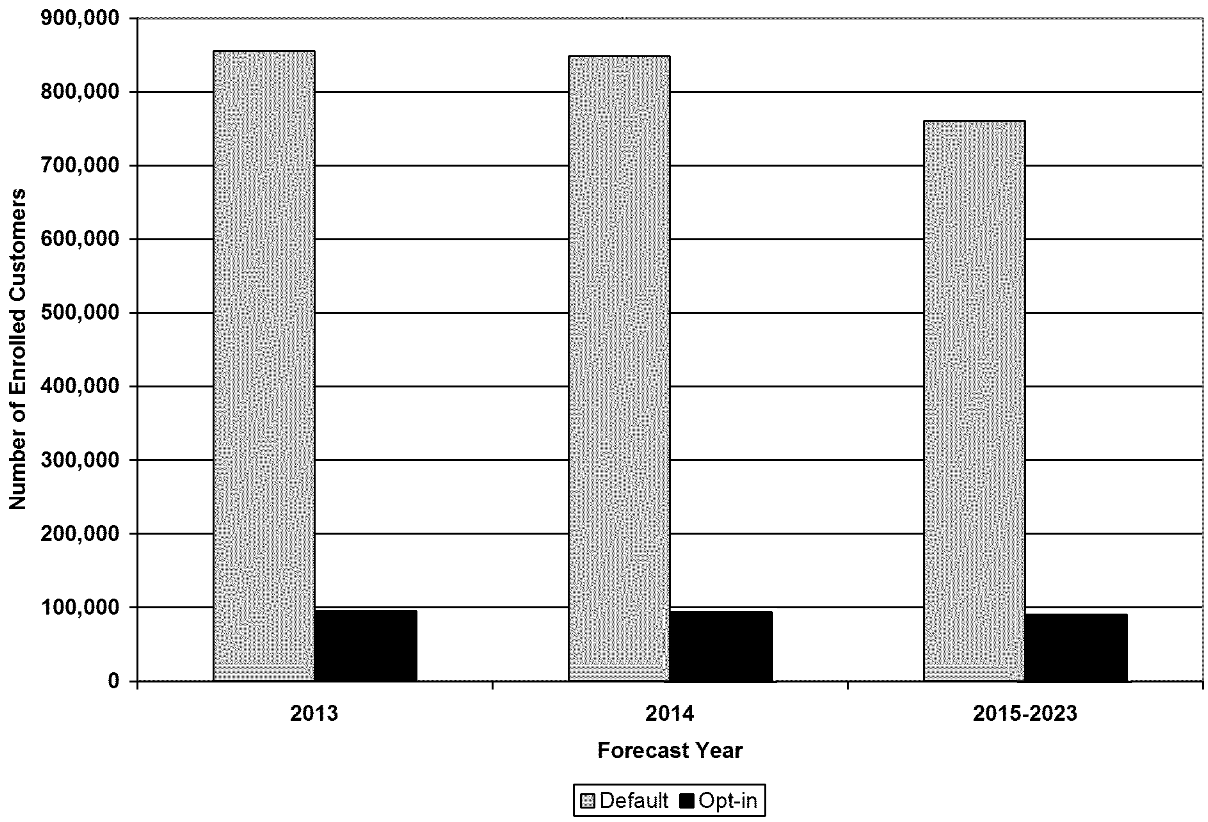
[5] While we observed ex post load impacts across a (somewhat narrow) range of temperatures (i.e., the different event days), the relationship between estimated load impacts and event-day temperatures was not robust. That is, it varied substantially as we examined the data for different groupings of customers, in ways that indicatedthat the estimates did not serve as a reliable basis for varying load impacts across the ex ante scenarios.

at which point SCE assumes that enrollments are static through 2023. The enrollments are used to scale up the reference loads and load impacts for each required scenario and customer subgroup.

5.3 Enrollment Forecasts

Figure 5–1 shows SCE's forecast of August enrollments by year and notice type. SCE assumes an increase in notified customers into 2013 that tapers off in subsequent years due to customer attrition.

Figure 5–1: Number of Enrolled Customers in August of Each Forecast Year



5.4 Reference Loads and Load Impacts

We provide the following summary of the ex ante forecasts: the hourly profile of reference loads and load impacts for typical event days; the level of load impacts across years; and the distribution of load impacts by local capacity area. Results presented for both the "program-specific" case (in which all PTR customers are assumed to respond) and the "portfolio-level" case (in which customers dually enrolled in SDP and PTR are not assumed to participate in the PTR event).

Together, these figures provide a useful indication of the anticipated changes in the forecast load impacts across the various scenarios represented in the Protocol tables. All of the tables required by the Protocols are provided in an Appendix.

Figure 5–2 shows the program-level August 2015 forecast load impacts for a typical event day in a 1-in-2 weather year. Event-hour (1:00 to 6:00 p.m.) load impacts average 23.6 MW, which represents approximately 1.3 percent of the enrolled reference load. Figure 5–3 shows the same load impacts at the portfolio level (i.e., when all DR programs are simultaneously called, which excludes customers dually enrolled in SDP and PTR). On average, the load impacts are reduced by 5.2 MW (relative to the program-level load impact) to 18.4 MW and the percentage load impact goes down slightly to 1.2 percent.

Figure 5–2: Hourly Event Day Load Impacts for the Typical Event Day in a 1-in-2 Weather Year for August 2015, Program Level

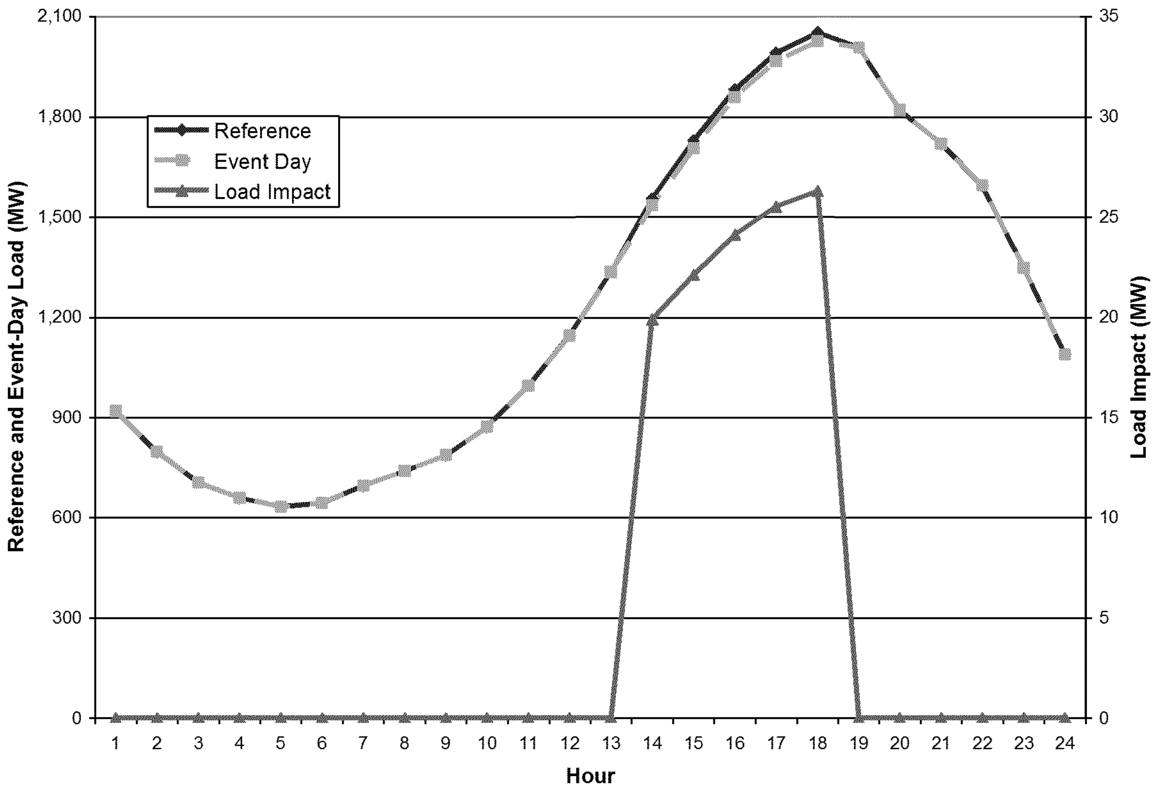


Figure 5–3: Hourly Event Day Load Impacts for the Typical Event Day in a 1-in-2 Weather Year for August 2015, Portfolio Level

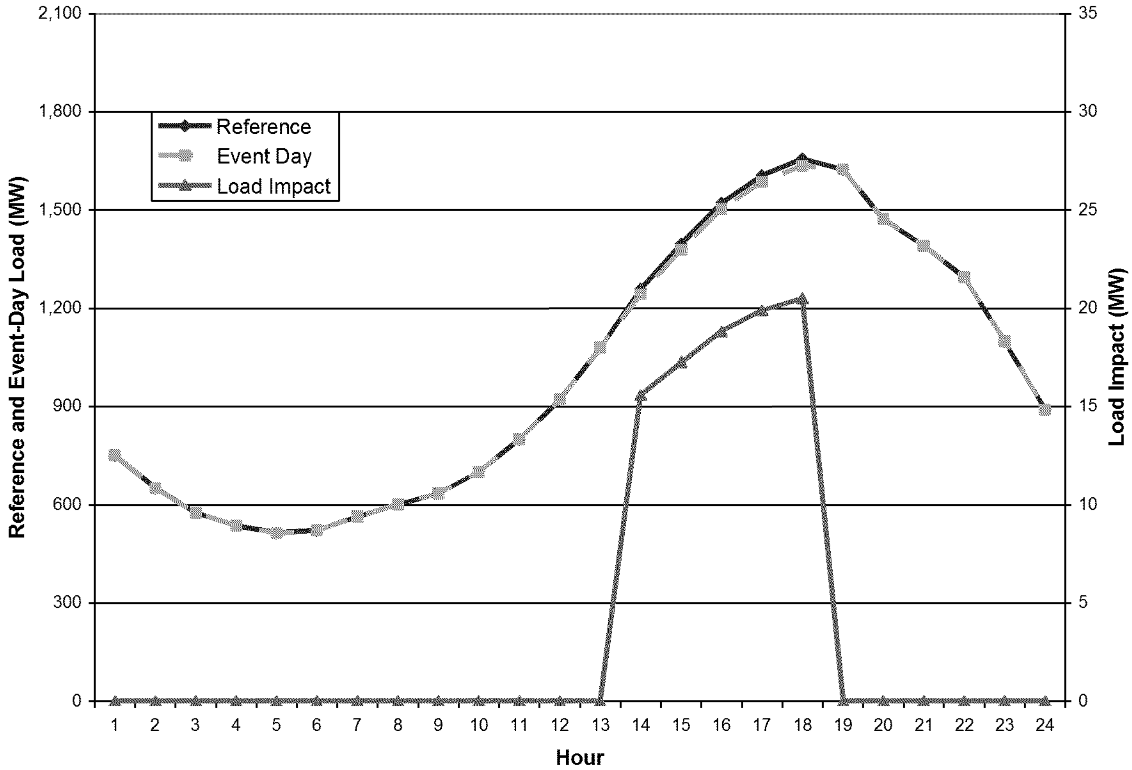


Figure 5–4 shows the share of load impacts by local capacity area, assuming a typical event day in an August 2015 1-in-2 weather year. Customers in the LA Basin account for the vast majority of the load impacts.

Figure 5–4: Share of Load Impacts by LCA for the August 2015 Typical Event Day in a 1-in-2 Weather Year

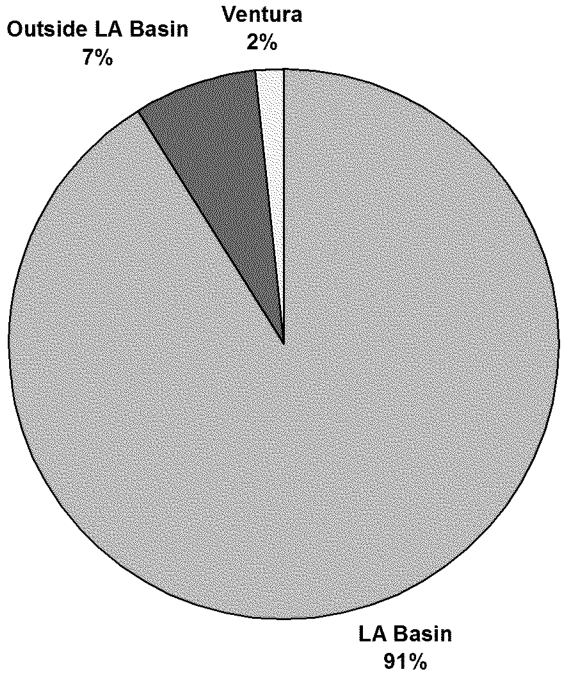


Figure 5–5 illustrates August load impacts for each forecast year across four scenarios, differentiated by 1-in-2 versus 1-in-10 weather conditions, and portfolio- versus program-level load impacts. Load impacts are slightly higher in the 1-in-10 weather years relative to the 1-in-2 years, with a larger difference between the program- and portfolio-based load impacts.

Figure 5–5: Average Hourly Ex Ante Load Impacts by Scenario and Year

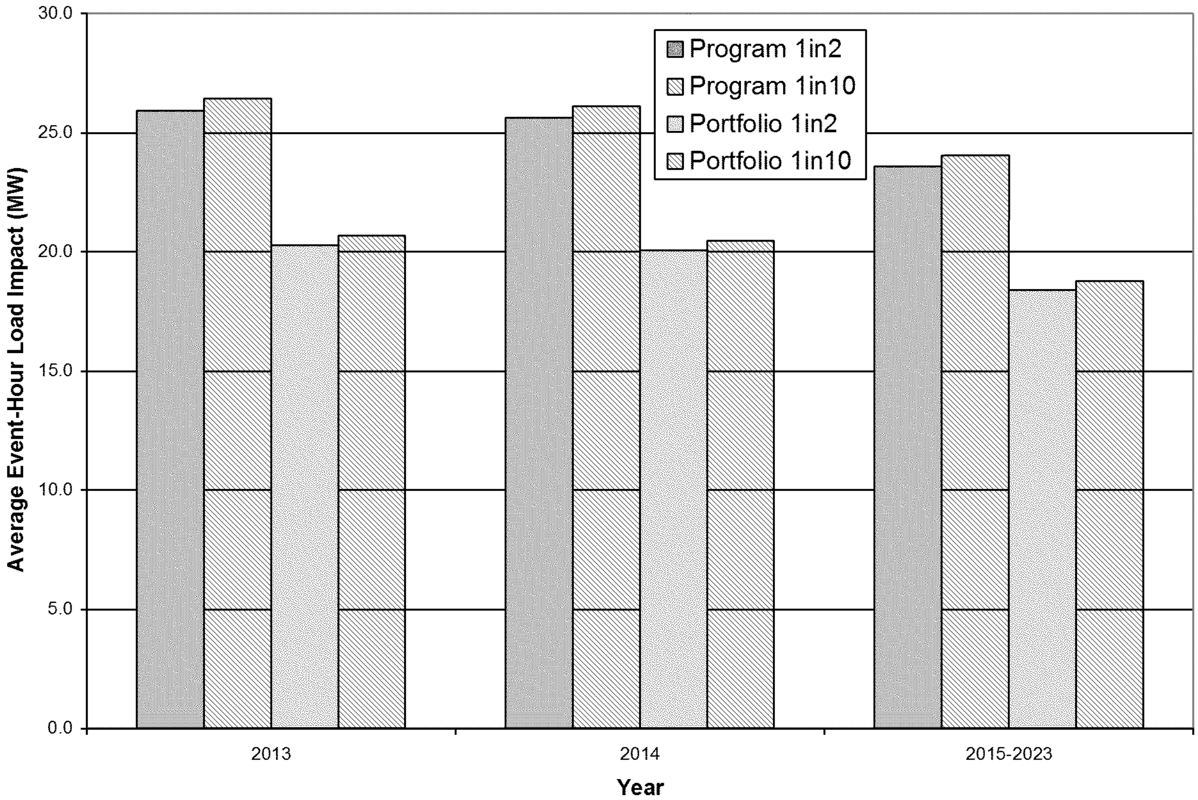


Figure 5-6 shows the share of total load and load impacts by notice type, calculated for the August 2013 peak day in a 1-in-2 weather year. Customers who opted into event notification account for a relatively small share of load (10 percent), but a much higher percentage of total load impacts (34 percent). This is consistent with the ex post load impacts, which showed higher percentage load impacts for opt-in notification customers relative to customers who were defaulted into event notification.

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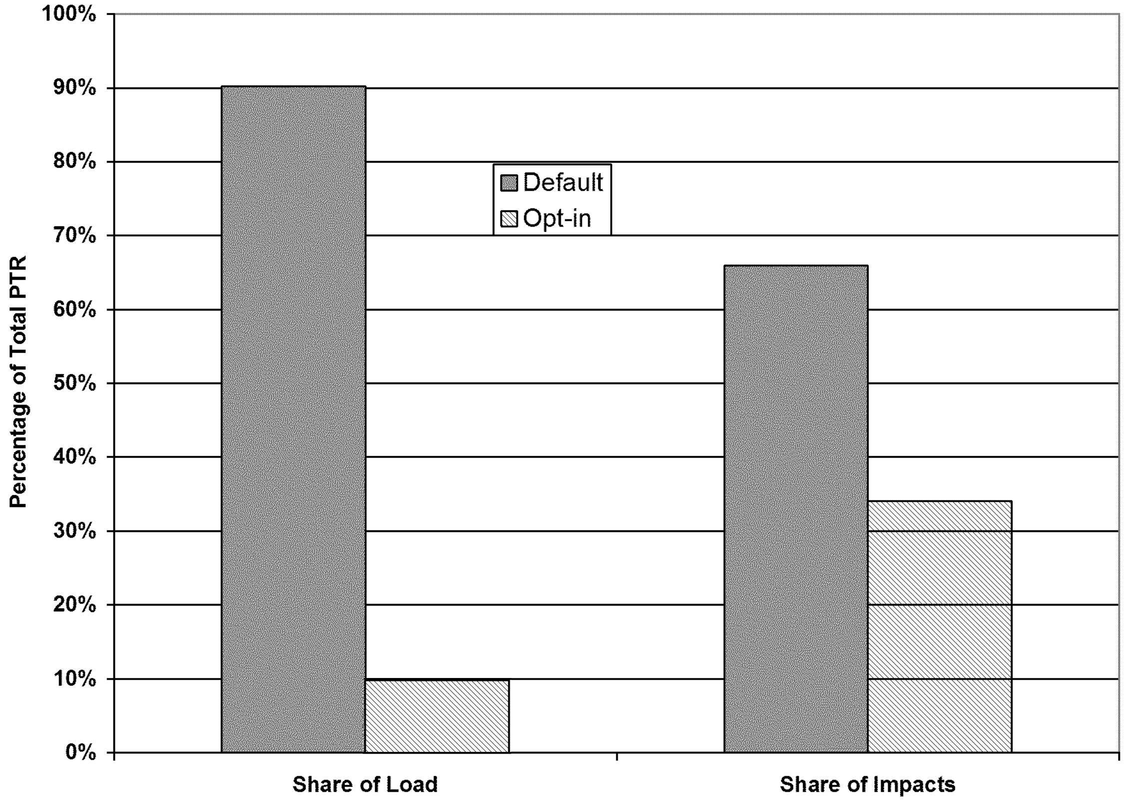
Figure 5–6: Share of Load and Load Impacts by Notice Type



6. CONCLUSIONS AND RECOMMENDATIONS

The *ex post* load impact results of this study suggest that greater event-day load reductions from the PTR (SPD) program may be achieved by educating customers, making them more aware of the program and its potential benefits, and developing strategies to encourage them to sign up to receive event notifications.

Our results for customers who were defaulted into notification, which indicate small and not statistically significant estimated load reductions for these customers, suggest that expanding default notification may have limited benefits (but no detrimental effects) on program performance.

A continuing measurement challenge will be to refine methods for estimating small load impacts among large groups of customers. Exploring a combination of customer-level load analysis and customer surveys may provide insights into characteristics of customers most likely to respond to PTR events.

APPENDIX A. MODEL SELECTION AND VALIDITY ASSESSMENT

A.1 Model Specification Tests

A range of model specifications were tested before arriving at the model used in the ex post load impact analysis. The basic structure of the model is shown in Section 3.3. The tests are conducted using data by customer group, where customer groups are defined by region (coastal or inland), and whether they opted to receive an event alert (versus being defaulted into event notification).

The model variations are based on differing methods of characterizing weather conditions. We tested 18 different combinations of weather variables. The weather variables include: heat index (HI)[6]; the 3-hour moving average if HI; temperature-humidity index (THI)[7]; the 3-hour moving average of THI; the 24-hour moving average of THI; cooling degree hours (CDH)[8], including both a 60 and 65 degree Fahrenheit threshold; the 3-hour moving average of CDH; the 24-hour moving average of CDH; and the one-day lag of cooling degree days (CDD)[9], including both a 60 and 65 degree Fahrenheit threshold. A list of the 18 combinations of these variables that we tested is provided in Table A–1.

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[6] HI = $c_1 + c_2T + c_3R + c_4TR + c_5T^2 + c_6R^2 + c_7T^2R + c_8TR^2 + c_9T^2R^2 + c_{10}T^3 + c_{11}R^3 + c_{12}T^3R + c_{13}TR^3 + c_{14}T^3R^2 + c_{15}T^2R^3 + c_{16}T^3R^3$, where T = ambient dry-bulb temperature in degrees Fahrenheit and R = relative humidity (where 10 percent is expressed as "10"). The values for the various c's may be found here: http://en.wikipedia.org/wiki/Heat_index.

[7] THI = T – 0.55 x (1 – HUM) x (T – 58) if T>=58 or THI = T if T<58, where T = ambient dry-bulb temperature in degrees Fahrenheit and HUM = relative humidity (where 10 percent is expressed as "0.10").

[8] Cooling degree hours (CDH) was defined as MAX[0, Temperature – Threshold], where Temperature is the hourly temperature in degrees Fahrenheit and Threshold is either 60 or 65 degrees Fahrenheit. Customer-specific CDH values are calculated using data from the most appropriate weather station.

[9] Cooling degree days (CDD) are defined as MAX[0, (Max Temp + Min Temp) / 2 – Threshold], where Max Temp is the daily maximum temperature in degrees Fahrenheit and Min Temp is the daily minimum temperature. Customer-specific CDD values are calculated using data from the most appropriate weather station.

Table A–1: Weather Variables Included in the Tested Specifications

Model Number	Included Weather Variables
1	HI
2	HI, HI_MA3
3	HI, HI_MA3, LagCDD65
4	CDH60, LagCDD60
5	CDH65, LagCDD65
6	CDH65, CDD65, LagCDD65
7	HI, CDD60, LagCDD60
8	THI, CDD60, LagCDD60
9	THI, CDD65, LagCDD65
10	CDH60, CDH60_MA3, LagCDD60
11	CDH65, CDH65_MA3, LagCDD65
12	THI, THI_MA3, LagCDD65
13	CDH60_MA3, CDH60_MA24
14	CDH65_MA3, CDH65_MA24
15	THI_MA3, THI_MA24
16	CDH60_MA3, LagCDD60
17	CDH65_MA3, LagCDD65
18	THI_MA3, LagCDD65

The model variations are evaluated according to two primary validation tests:

1. Ability to predict usage on event-like *non-event days*. Specifically, we identified a set of days that were similar to event days, but were not called as event days (i.e., "test days"). The use of non-event test days allows us to test model performance against known "reference loads," or customer usage in the absence of an event. We estimate the model excluding one of the test days and use the estimates to make out-of-sample predictions of customer loads on that day. The process is repeated for all of the test days. The model fit (i.e., the difference between the actual and predicted loads on the test days, during afternoon hours in which events are typically called) is evaluated using mean absolute percentage error (MAPE) as a measure of accuracy, and mean percentage error (MPE) as a measure of bias.
2. Performance on *synthetic* event days (e.g., event-like non-event days that are treated as event days in estimation), to test for "event" coefficients that demonstrate statistically significant bias, as opposed to expected non-significance, since customers have no reason to modify usage on days that are not actual events. This is an extension of the previous test. The same test days are used, with a set of hourly "synthetic" event variables included in addition to the rest of the specification to test whether non-zero load impacts are estimated for these days. A successful test involves synthetic event load impact coefficients that are not statistically significantly different from zero.

A.1.1 Selection of Event-Like Non-Event Days

In order to select event-like non-event days, we created an average weather profile using the load-weighted average across customers in each region, each of which is associated with a weather station. We "scored" each day (separately for weekends and weekdays) by comparing the temperatures and relative humidity values to the values for each event day. For example, we calculated the following statistic for each day relative to the first day: abs($Temp_t$ – $Temp_{Evt}$) / StdDev($Temp$). A similar score was also calculated for humidity and the sum of the two scores was used to rank the days. We selected the five lowest-scoring days (low scores indicate greater similarity to the event day) for each event day. Days were excluded from the list as necessary (e.g., to exclude other event days).

Table A–2: List of Event-Like Non-Event Days

Date	Day of Week
7/19/2012	Thursday
7/20/2012	Friday
8/7/2012	Tuesday
8/8/2012	Wednesday
8/17/2012	Friday
8/20/2012	Monday
8/30/2012	Thursday
9/6/2012	Thursday

A.1.2 Results from Tests of Alternative Weather Specifications

As described above, we tested 18 different sets of weather variables for each of 4 customer sub-groups. The tests are conducted by estimating one model for every customer group (4), specification (18), and event-like day (8). Each model excludes one event-like day from the estimation model and uses the estimated parameters to predict the usage for that day. The MPE and MAPE are calculated across the event windows of the withheld days.

Table A–3 shows the mean percentage error (MPE) and mean absolute percentage error (MAPE) for the selected ("winning") specification for each utility and program, which was specification 6 from Table A–1 for the Coastal region (which uses the CDH65 and current and lagged values of CDD65) and specification 2 (which uses HI and its 3-hour moving average) for the Inland region. The values in parentheses are the standard deviations of the statistic across the 18 specifications. The bias (measured using MPE) tends to be positive, indicating a tendency for the model to overstate true baselines. However, the bias is fairly small, particularly for the Inland customer groups.

Model error, as measured by MAPE, ranges from 2.8 percent to 6.2 percent across the customer groups. As was the case with the bias measure, the models for Inland customers perform better than the models for Inland customers.

Table A–3: Specification Test Results for the "Winning" Model

Region	Notice Type	MPE	MAPE
Coastal	Opt-in	0.9% (0.8%)	5.5% (0.5%)
	Default	0.4% (1.0%)	6.2% (1.0%)
Inland	Opt-in	0.2% (0.6%)	2.8% (1.4%)
	Default	0.1% (0.5%)	2.7% (1.2%)

For each specification, we estimated a single model that included all of the days (i.e., not withholding any event-like days), but using a single set of actual event variables (i.e., a 24-hour profile of the average event-day load impacts). The results of these tests demonstrate the implication on estimated load impacts associated with each tested specification.

Figures A–1 through A–4 show the estimated hourly load impacts for each of the 18 level models by notice and climate zone. The bold black line represents the selected specification. As one might expect, there is more variability in the estimated load impacts for the two default notice groups (in Figures A–2 and A–4). That is, our expectation is that they would be less demand responsive than the opt-in notification customers, which could lead to less robust load impact estimates across alternative specifications.

Note that several of the load impact profiles in Figure A–2 (for the Coastal default notice customers) appear to show considerably more demand response than is estimated in the selected specification. However, these specifications also had quite high MPE values, indicating significant bias in the models.

Figure A–1: Average Event-Hour Load Impacts by Specification: *Coastal Opt-in Notice*

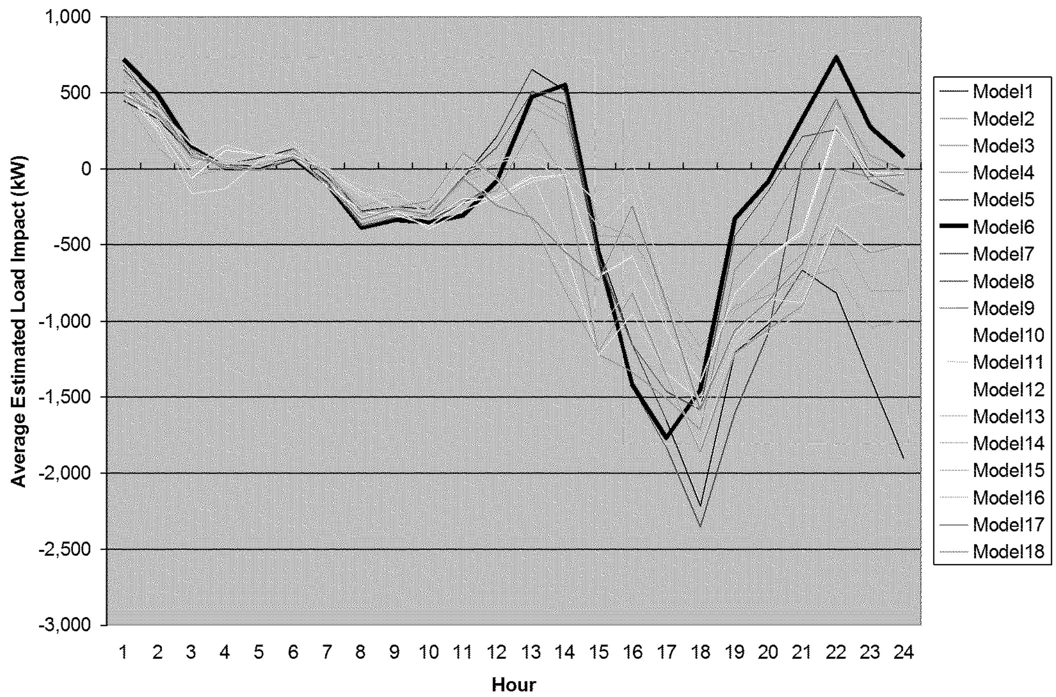


Figure A–2: Average Event-Hour Load Impacts by Specification, *Coastal Default Notice*

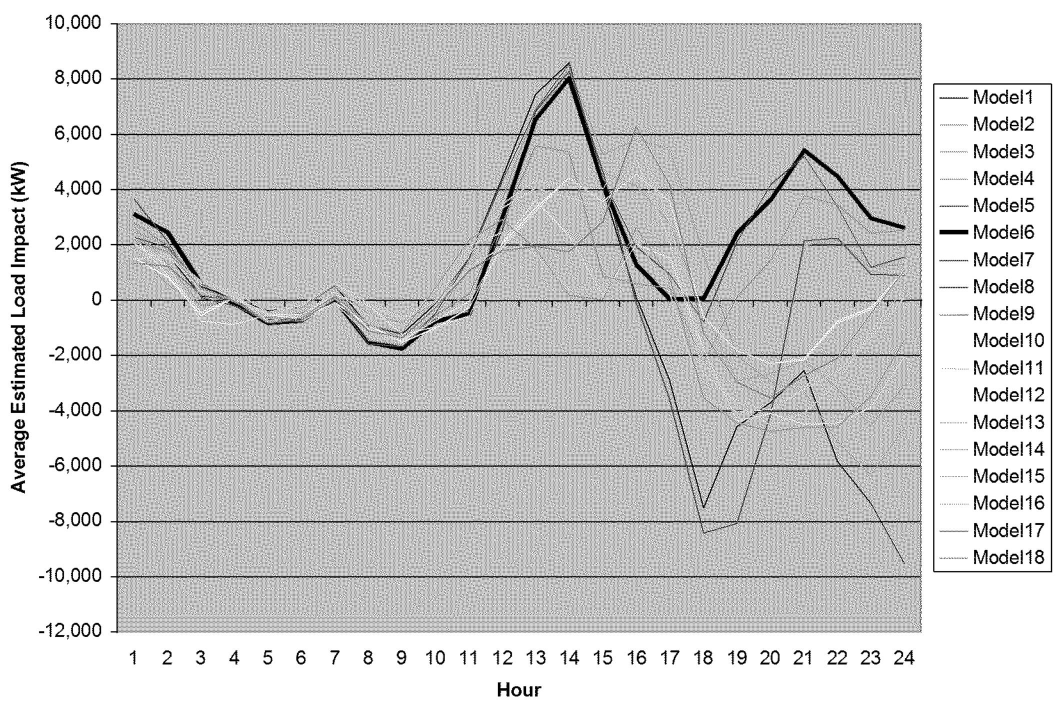


Figure A–3: Average Event-Hour Load Impacts by Specification, *Inland Opt-in Notice*

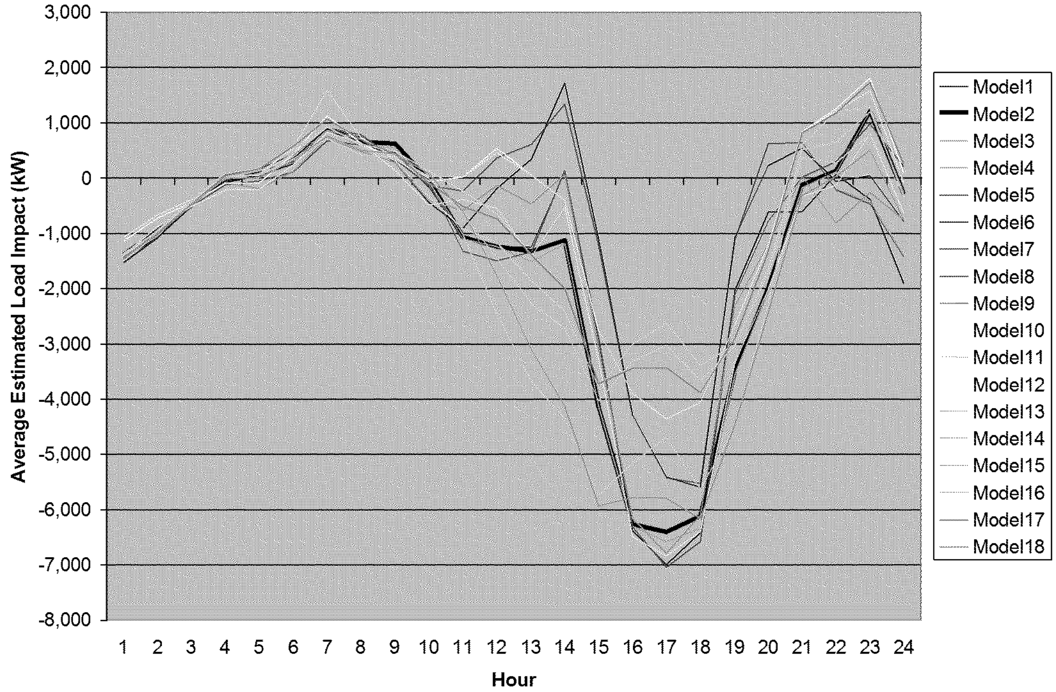
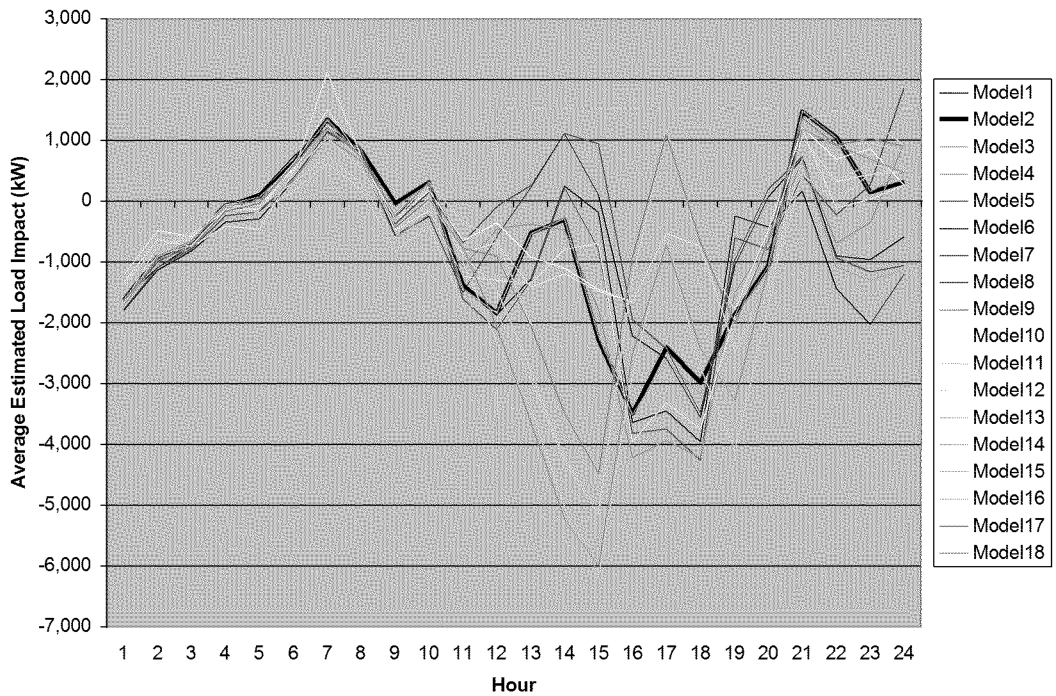


Figure A–4: Average Event-Hour Load Impacts by Specification, *Inland Default Notice*



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A.1.3 Synthetic Event Day Tests

For the specification selected from the testing described in Section A.1.2, we conducted an additional test. The selected specification was estimated on the aggregate customer data, including a set of 24 hourly "synthetic" event-day variables. These variables equaled one on the days listed in Table A–1, with a separate estimate for each hour of the day.

If the model produces synthetic event-day coefficients that are not statistically significantly different from zero, the test provides some added confidence that our actual event-day coefficients are not biased. That is, the absence of statistically significant results for the synthetic event days indicates that the remainder of the model is capable of explaining the loads on those days.

Table A–4 presents the results of this test for each customer group, showing only the coefficients during a typical event window of hours-ending 15 through 18. The values in parentheses are p-values, or measures of statistical significance. A p-value of less than 0.05 indicates that the estimated coefficient is statistically significantly different from zero with 90 percent confidence. The p-values in Table A–4 are uniformly higher than this standard, indicating that each model "passes" this test (i.e., the estimated coefficients on the synthetic event day variables are *not* statistically significant).

Table A–4: Synthetic Event-Day Tests by Customer Group

Hour	Coastal		Inland	
	Opt-in	Default	Opt-in	Default
15	2,126 (0.223)	7,087 (0.422)	3,526 (0.319)	2,555 (0.542)
16	1,734 (0.359)	6,702 (0.524)	1,136 (0.719)	-578 (0.877)
17	1,480 (0.418)	4,754 (0.663)	-690 (0.822)	-1,443 (0.704)
18	880 (0.588)	3,232 (0.723)	-179 (0.954)	-81 (0.984)

ADDITIONAL APPENDICES

The following Appendices accompany this report. Both are Excel files that produce the tables required by the Protocols.

Study Appendix B — SCE PTR *Ex-Post* Load Impact Tables
Study Appendix C — SCE PTR *Ex-Ante* Load Impact Tables