The Brattle Group

BGE's SMART ENERGY PRICING PILOT SUMMER 2008 IMPACT EVALUATION

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Ahmad Faruqui, Ph.D.
Sanem Sergici, Ph.D.

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Ahmad Faruqui
Sanem Sergici

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1. Executive Summary

The Brattle Group was retained by Baltimore Gas & Electric Company (BGE) in December 2006 to assist in the design of a dynamic pricing pilot program to develop assessments of the likely impact of a variety of dynamic pricing programs on BGE residential customer load shapes. The residential pilot program, Smart Energy Pricing (SEP) Pilot, was subsequently approved by the Maryland Public Service Commission and successfully implemented in the summer of 2008. This report presents the results from the impact evaluation of the BGE's SEP Pilot in the summer of 2008.

The SEP Pilot featured some 1,375 residential customers and ran from June 1, 2008 through September 30, 2008. Over a thousand customers were placed on a dynamic pricing rider or tariff in combination with two technologies, an in-home display known as the Energy Orb and a switch for cycling central air conditioners. These customers served as the treatment group. The remainder stayed on the standard tariff and served as a control group. Hourly usage was recorded for customers in both groups during the pilot to determine if the treatment group used less during the more expensive periods. In addition, to assess for any pre-existing difference in the groups, hourly usage was also recorded during a pre-pilot phase. The experimental design is summarized in Table 2.4.

The SEP Pilot tested several pricing structures. BGE's standard rate is a flat, seasonal, volumetric rate that includes a fixed customer charge. Two types of time-varying tariffs were tested in the pilot. The first one was a dynamic peak pricing (DPP) tariff, where the price during the peak period (which ran from 2 pm to 7 pm) during a small number of critical peak days was raised by a factor of about nine compared to the standard rate. At the same time, to preserve revenue neutrality, the off-peak price was lowered by six cents per kWh. On non-critical weekdays, customers faced a two-period time-of-use (TOU) rate. The price during the peak hours was roughly equal to the standard rate but the off-peak price was lower, as noted above. Prices during all weekend and holidays hours were off-peak prices.

The second pricing option was the peak time rebate (PTR) rider where customers were given an opportunity to earn a rebate during the peak period on critical peak days by lowering usage. They paid the standard rate, but were able to earn a rebate for lowering their usage during critical peak events. Two variations of the PTR were tested in order to estimate price elasticities. One featured a relatively low rebate amount and was termed PTRL and other featured a relatively high rebate amount and was termed PTRH. During critical days, the PTRL rate provided a rebate that was about nine times higher than the standard rate and thus was comparable to the DPP rate. The PTRH rate provided a rebate that was about 12.5 times greater than the standard rate.

BGE called 12 critical peak days during the course of the pilot period. The specific dates on which these events were called are shown in Table 3.1 along with the weather conditions that prevailed on those dates. To measure the persistence of savings, and to determine if customers were fatigued by dynamic pricing, some events were called on adjacent days. Customers were notified on a day-ahead basis that the next day would be a critical day. Several means of communication were used, including a phone call, email, and text messages. On critical days, SEP participants had a strong price incentive to either curtail peak usage or to shift it to the less expensive peak period.

Using the data from the pilot participants and the control group customers both before and during the pilot period, we estimated demand models to determine the load impacts from the programs tested in the SEP Pilot. Overall, the load reduction during the critical peak hours varied across all program types, from a low of about 18 percent to a high of about 33 percent. These estimated impacts were statistically significant at the five percent level.[1] In the absence of enabling technologies, the reduction in critical peak period usage ranged from 18 to 21 percent. When the Energy Orb was brought into the picture, critical peak period load reduction impacts ranged from 23 to 27 percent. When the switch on the central air conditioner was added to the Energy Orb, the impacts ranged from 29 to 33 percent. There was clear evidence that enabling technologies boosted the impact of the dynamic pricing rates.

It is also important to note that the substitution elasticities for DPP, PTRL, and PTRH rates were not found to be statistically distinguishable from each other when tested separately in the estimation equations. This result has an important implication that the SEP customers show the same responsiveness to dynamic pricing whether it is expressed as a price increase during the critical hours or the availability of a peak time rebate.

Section 2 of this report describes the experimental design of the SEP. Section 3 summarizes the analytical methods and data used in the estimation of the load impacts from the SEP treatments. Section 4 summarizes the impact evaluation results.

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[1] Statistical significance at the five percent level implies that there is only five percent probability of incorrectly rejecting the null hypothesis that the estimated value is equal to zero, *i.e.*, SEP rates do not lead to load reductions.

2. Background and Overview

2.A SEP EXPERIMENTAL DESIGN

BGE conducted its residential dynamic pricing pilot program, called the Smart Energy Pricing (SEP) Pilot, in the summer of 2008. It ran from June 1, 2008 through September 30, 2008. BGE tested three dynamic pricing structures in the SEP: a dynamic peak pricing (DPP) tariff, which is essentially a critical peak price (CPP) tariff that is combined with a TOU rate, and two peak time rebate (PTR) riders, one testing a low rebate level (PTRL) and the other testing a high rebate level (PTRH). BGE also tested the impacts of two different technologies, the Energy Orb and a switch for cycling air conditioners in conjunction with the three dynamic pricing options described above. Three different pricing structures and two technologies yielded eight program combinations (DPP with the Energy Orb technology was not tested in the pilot).

2.B RATE DESIGN

The average all-in rate for the residential BGE customers who were on the standard tariff was \$0.15/kWh during the SEP Pilot period. Customers in the control group paid \$0.15/kWh during the pilot period regardless of their load profile. The SEP participants were subject to one of the three following dynamic rate designs:

1. Dynamic Peak Pricing (DPP): Under the DPP rate design, the hours between 2 pm through 7 pm on non-holiday weekdays were designated as the peak period and all the remaining hours were designated as the off-peak period. On 12 critical peak days that were called by BGE, the peak hours would become the critical peak hours. The DPP rates are presented in Table 2.1.

Table 2.1: DPP Rate Design (June 01, 2008 – September 30, 2008)

Time / Day	Category	Rate ($/kWh)
2 p.m.-7 p.m. Weekdays	Peak	0.14
2 p.m.-7 p.m. Weekdays	Critical Peak	1.30
Weekends, Holidays & 7 p.m.-2 p.m. Weekdays	Off-peak	0.09

Note: The SEP DPP prices include generation, transmission, and distribution charges. They can be converted into all-in prices by adding the customer charge of \$ 7.50 per month, which translates into \$0.009/kWh for the average customer.

2. Peak Time Rebate- Low (PTRL): Under the PTRL rate design, the SEP participants were still subject to the standard BGE rates. However, on the 12 critical peak days, between hours 2 pm and 7 pm, they had the opportunity to receive a rebate if they can reduce their consumption below their typical usage during these hours. Participants

received $1.16 for every kWh of load reduction below their baseline usage. The PTRL rates are presented in Table 2.2.

3. Peak Time Rebate- High (PTRH): Under the PTRH rate design, the SEP participants were also subject to the standard BGE rates. However, on the 12 critical peak days, between hours 2 pm and 7 pm, they had the opportunity to receive a rebate if they reduced their consumption below their typical usage during these hours. Participants received $1.75 for every kWh of load reduction below their baseline usage. The PTRH rates are also presented in Table 2.2.

Table 2.2: PTRL and PTRH Rate Designs (June 01, 2008 – September 30, 2008)

Time / Day	Category	Rate ($/kWh)	Rebate per kWh Reduction Below Baseline Usage ($)
2 p.m.-7 p.m. Weekdays	Standard	0.15	-
2 p.m.-7 p.m. Weekdays	Critical Peak	0.15	1.16 (PTRL) , 1.75 (PTRH)
Weekends, Holidays & 7 p.m.-2 p.m. Weekdays	Standard	0.15	-

Note: The standard rate is the average all-in rate during the pilot period.

BGE called 12 critical peak demand days in the summer of 2008. The SEP participants were notified of the critical peak days on a day-ahead basis through one or more of the following 15 options: telephone messages (up to five different numbers), e-mail communication (up to five different addresses), and SMS text messages (up to five different numbers). In addition, certain customers were notified by their Energy Orb.

2.C TECHNOLOGY SECTION

The SEP also tested the effectiveness of enabling technologies in facilitating the demand response when the dynamic rates are offered in conjunction with the enabling technologies. In order to be able to tell apart the impacts of the enabling technologies from that of the prices alone, each rate design was tested with and without the technology options.

The SEP tested the implications of two enabling technologies. One was the Energy Orb, a sphere that emits different colors to signal off-peak, peak and critical peak hours. This is a visual aid that notifies customers of the time period and makes it convenient for them to respond to the more expensive hours. BGE provided a subset of the customers with the Energy Orbs.

The other technology tested in the SEP was a switch on the compressor of the central air conditioner. Through the A/C switch, BGE cycled the air conditioners of a subset of the program participants during the critical peak hours, using a 50 percent cycling strategy. That is, during a critical event, customers who had the switch had their typical air conditioning usage decreased by 50 percent. BGE did not test the A/C switch as a standalone technology in this pilot, but rather it was tested together with the Energy Orb. In other words, BGE provided a subset of the SEP participants both with the Energy Orb and the A/C switches.

With three different dynamic rate structures and two different enabling technology options, BGE tested eight different rate-technology combinations in the SEP Pilot. The number of combinations is eight rather than nine since the DPP rate with Energy Orb combination was not tested in the pilot. These combinations are shown in Table 2.3.

Table 2.3: Rate and Technology Combinations Tested in the SEP Pilot

Rate Design	Enabling Technology	Abbreviation
DPP	None	DPP
DPP	Energy Orb and A/C Switch	DPP_ET_ORB
PTRL	None	PTRL
PTRL	Energy Orb Only	PTRL_ORB
PTRL	Energy Orb and A/C Switch	PTRL_ET_ORB
PTRH	None	PTRH
PTRH	Energy Orb Only	PTRH_ORB
PTRH	Energy Orb and A/C Switch	PTRH_ET_ORB

2.D SAMPLE DESIGN

The SEP Pilot featured 1,375 customers of which 1,021 customers were the program participants and constituted the treatment group while 354 customers constituted the control group. Table 2.4 presents the design of the SEP Pilot sample as of July 2008.

Table 2.4: The SEP Pilot Sample Design (as of July 2008)

Group	Treatment Group	Control Group	Total
DPP	148	-	148
DPP_ET_ORB	111	-	111
PTRL	126	-	126
PTRL_ORB	141	-	141
PTRL_ET_ORB	113	-	113
PTRH	127	-	127
PTRH_ORB	137	-	137
PTRH_ET_ORB	118	-	118
Total	**1021**	**354**	**1375**

2.D.1 Treatment Group Recruitment

BGE targeted 1,000 treatment customers to recruit for the SEP program. BGE recruited the SEP Pilot participants through direct mailing and follow-up phone calls. These treatment customers were recruited from three different samples:

1. Load Research Sample: There were 440 customers in the load research sample. BGE initially recruited 117 treatment customers from this sample but 33 of them later dropped out, leaving 84 customers to be recruited from the load research sample. Of the 33 who dropped out 24 changed their mind, five moved out, three had installation technical issues, and 1 became a tenant dwelling. Not all could be reached as to their decision to drop out, but some gave the reason as simple change of mind, signing up with a third party electric supplier, or participating in BGE's budget billing plan.

2. Interval Meter Test Sample: There were 200 customers in the Interval Meter Test Sample. BGE initially recruited 33 treatment customers from this sample but 5 of them later dropped out, leaving 28 customers recruited from the Interval Meter Test Sample.

The recruiting efforts from these two samples produced 112 treatment customers.

3. Additional Sample: To recruit the rest of the targeted 1,000 customers, BGE randomly selected an additional pool of 5,000 customers. There were certain restrictions to be involved in this sample as the goal was to fairly represent the population served by BGE, *i.e.*, time-of-use (TOU) customers as well as those who

buy power from retail energy service providers (ESPs) were excluded from the sample.[2] The rest of the treatment customers were recruited from this pool.

In the recruitment process, BGE first mailed information to the customers to notify them about the SEP and to invite them to join the pilot. Customers who received the mailings could contact BGE's hot line by email or telephone. BGE also used outbound calls to contact customers who did not respond. Ample information was provided in the mailing to clearly describe the pilot. It described the type of rate design and/or enabling technology to each customer who was invited to participate. The letter only discussed one specific rate group (*e.g.* PTR or DPP) and did not mention the other available group. Customers were offered a one time appreciation payment of $150 (for DPP) or $100 (for PTR) upon their completion of all requirements of the programs. Appendices 5 and 6 respectively provide program fliers and welcome package materials that were mailed out to the customers.

BGE sequentially recruited treatment customers for eight different treatment groups. The first wave of the recruitment effort was for Dynamic Peak Pricing (DPP) group. Once the target number of DPP customers was reached, BGE started to recruit customers into the Peak Time Rebate (PTR) group.

2.D.2 Control Group Recruitment

The recruiting process for the control customers followed a residual approach. Of the 440 customers in the Load Research Sample, BGE was able to reach by phone and recruit 117 into the treatment group. Of the 200 customers in the Interval Meter Test Sample, BGE was able to reach by phone and recruit 33 into the treatment group. Customers from these two sample groups who were not contacted or not recruited were assigned to the control group. This approach resulted in 354 control group customers in the sample as of July 2008.

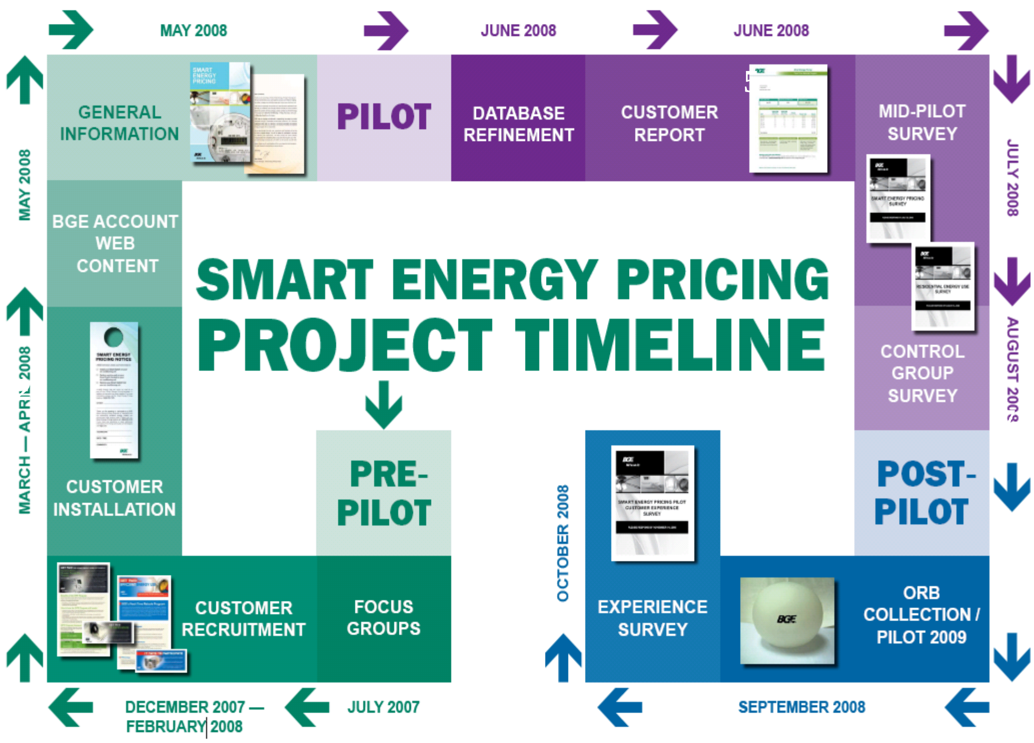
It's important to note that the control group customers were not aware of their involvement in the SEP Pilot. These customers were intended to serve as a proxy for the behavior of the treatment group customers had they not been in the treatment group, *i.e.*, to help define conditions in the "but-for" world.

[2] About two percent of BGE's residential customers are enrolled with ESPs. TOU customers represent about six percent of BGE's total residential base. TOU accounts typically are for relatively new construction and tend to have central air conditioners and higher average monthly usage than non-TOU accounts. The TOU accounts were omitted due to the complexities of adding dynamic pricing to TOU accounts, and because they represented a small fraction of the total accounts. Most likely, impacts for TOU accounts would be equal to or greater than for non-TOU accounts.

2.D.3 Treatment Group Education

One of the factors that determine the success of a pilot program is the awareness and education of the pilot participants. Figure 2.1 presents the SEP pilot timeline and BGE's educational campaign for the program participants.

Figure 2.1 BGE SEP Pilot Timeline



1. Customer Recruitment: A flyer was designed for each of the programs, Dynamic Peak Pricing (DPP) and Peak Time Rebate (PTR), to be used in the customer recruitment effort. Both flyers provided a general program overview including program rates, potential critical peak hours, and ways to reduce electricity consumption in order to save money on the program. These materials were followed up with a recruitment phone call giving the customer a chance to learn more about the program and sign up to participate.

2. Installation Information: Following recruitment, it was necessary to install a new meter at all of the customer premises in order to record electricity usage on a 15-minute interval basis, unless the customer already had an interval meter. Some customers opted to participate with a Smart Switch. In most cases the customer did not need to be present for either of the installations to occur so technicians posted a door-hanger to notify them of the upgrades that were made and listed a contact number should they have any questions.

3. Web Account Content: When SEP participants logged into their BGE online account, they could access information about Smart Energy Pricing. A website was created for each of the treatment groups so customers could receive program specific information. Critical peak event notifications were also posted on these websites to serve as an additional form of customer notification.

4. Welcome Package: All SEP Participants received a "welcome package" prior to the start of the pilot. The package was comprised of a main section featuring a welcome message, ways to save, and frequently asked questions. Each package was then customized for the eight treatment groups using program and technology specific inserts. The program inserts included information about the new pricing design and what customers should expect to see on their summer bills. The technology inserts provided details on how the Energy Orb and Smart Switch operated and would enable the customer to save more on the program.

5. Savings Report: Following critical peak events, PTR customers were sent a report summarizing their savings for the most recent event as well as their overall program savings. This enabled customers to understand how their actions to reduce energy consumption translated into rebate savings. Similarly, DPP customers received a savings report, but on a monthly basis. This method for reporting was chosen since DPP savings is the result of shifting electricity usage to off peak hours as well as reducing peak and critical peak hour consumption over a period of time. DPP savings reports were sent to participants around the same time that they received their bill.

6. Mid-Pilot Survey: Participants were asked to complete an appliance survey midway through the pilot, with a $25 incentive payment. The information was collected in order to identify trends and understand how various appliances may have impacted customers' ability to reduce consumption.

7. Control Group Survey: Control group customers were also asked to complete an appliance survey, with a $25 incentive payment. As with the pilot participant survey, this information was collected in order to better understand the consumption patterns of the control group customers.

8. Orb Collection & 2009 Pilot: Toward the end of the summer of 2008, customers were informed that the program would be offered again the following summer with more information to come. DPP participants were also asked to return their Energy Orbs. PTR customers were allowed to keep the Orbs since the second pilot would only have a PTR pricing option and those devices would not require reprogramming.

9. Experience Survey: Following the pilot, participants were asked to complete a survey summarizing their experience on the program. For completing the survey, customers received a $25 incentive payment. The survey revealed that almost all participants would like to continue the program. The feedback was also considered in developing the 2009 pilot program.

3. Load Impact Analysis Methodology

Our analytical approach to evaluating the load impacts of the SEP Pilot is based on the application of econometrics and microeconomic theory to data collected in the SEP. We first specify electricity demand models that represent the electricity consumption behavior of the BGE customers. Second, we use econometric methods (regression analysis) to estimate and parameterize the models. Finally, we simulate the impact of the treatments that were deployed in the pilot as well as intermediate treatments that could be deployed in the post-pilot phase.

Demand models are used to estimate the demand response impacts of each SEP pricing option, as opposed to alternative methods such as analysis of variance and covariance, in part because they allow for estimation of the price elasticities. This capability is vital to being able to estimate the impact of prices other than those used in the pilot.

Section 3.A provides an overview of the model specification and estimation. Section 3.B provides an analytical description of the demand models as well as the substitution elasticities estimated from the demand models.

3.A MODEL SPECIFICATION AND ESTIMATION

We employ a widely used model, the constant elasticity of substitution (CES) demand model, to estimate customer demand curves and price elasticities. For a two-period rate structure, the CES model consists of two equations. The first equation models the ratio of peak to off-peak quantities as a function of the ratio of peak to off-peak prices and other terms, and the second models average daily electricity consumption as a function of average daily price of electricity and other terms. The two equations constitute a system for predicting electricity consumption by time period where the first equation essentially predicts the changes in the load shape caused by changing peak to off-peak price ratios and the second equation predicts the changes in the level of daily electricity consumption caused by changing average daily electricity price. New level of daily electricity consumption implied by the second equation is partitioned between peak and off-peak periods using the new load shape implied by the first equation.

BGE metered the hourly usage of the treatment and control group customers both before and during the pilot period. This data compilation yielded a dataset of 1,375 customers starting in April, 2008 and extending through September 30, 2008. This cross-sectional time series dataset of the SEP Pilot participants and control group customers is employed to estimate our demand models. We use a “fixed-effects” estimation routine to estimate this demand system. Fixed effects estimation uses a data transformation method that removes any unobserved time-invariant effect that has a potential impact on the dependent variable. By estimating a fixed effects model, we effectively control for all customer specific characteristics that don’t vary over time and isolate their impact on the dependent variable. This approach is equivalent to “dummy variable regression” approach where one introduces individual dummy variables for all the customers that are included in the regression.[3] Fixed-effects estimation routine controls for the unobserved time-invariant variables that are likely to impact the dependent variable. However, there are also several observed variables that may affect the level of the dependent variable and therefore need to be explicitly controlled for in the model. We discuss these variables and more generally the econometric specifications of the substitution and daily demand equations in the next section.

Substitution Demand Equation

As stated earlier, the substitution equation captures the consumption substitution behavior of the customers between peak (or critical peak on the event days) and off-peak periods.

The substitution equation takes the following functional form:

$$\begin{aligned}
\ln\left(\frac{Peak_kWh}{OffPeak_kWh}\right)_{it} &= \alpha_0 + \alpha_1 THI_DIFF_t + \alpha_2 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} + \alpha_3 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xTHI_DIFF_t \\
&+ \alpha_4 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xORB_i + \alpha_5 \ln\left(\frac{Peak_Price}{OffPeak_Price}\right)_{it} xET_ORB_i + \sum_{k=1}^{6} \delta_k (THI_DIFF_t xD_Month_k) \\
&+ \alpha_6 D_TreatPeriod_t + \alpha_7 D_TreatPeriod_t xTreatCustomer_i + \sum_{k=1}^{6} \beta_k D_Month_k + \sum_{k=1}^{12} \gamma_k D_CPP_k \\
&+ \alpha_8 D_WEEKEND_t + v_i + u_{it}
\end{aligned}$$

where:

$\ln\left(\frac{Peak\_kWh}{OffPeak\_kWh}\right)_{it}$: Logarithm of the ratio of peak to off-peak load for a given day

THI_DIFF_t : The difference between average peak and average off-peak THI.
THI= 0.55 x Drybulb Temperature + 0.20 x Dewpoint + 17.5

$\ln\left(\frac{Peak\_Price}{OffPeak\_Price}\right)_{it}$: Logarithm of the ratio of peak to off-peak prices for a given day

$\ln\left(\frac{Peak\_Price}{OffPeak\_Price}\right)_{it} xTHI\_DIFF_t$: Interaction of ratio of peak to off-peak prices and *THI_DIFF* for a given day

[3] Both approaches will produce the same coefficient estimates and all the other statistical estimates will be the same. The only difference between two approaches will be in level of the R-squares. Fixed-effects estimation only represents the amount of time variation in the dependent variable that is explained by the time variation in the explanatory variables (Wooldridge, 2003). In other words, while fixed-effects estimation doesn't take into account the explained variation by the individual customer dummies, the dummy variable regression does takes into the explanatory power of the individual dummies. For that reason, R-squared obtained from the dummy variable regression will be larger.

$\ln(\frac{Peak\_\text{Price}}{OffPeak\_\text{Price}})_{it} xORB_i$: Interaction of ratio of peak to off-peak prices and *ORB* for a given day.
ORB: is equal to 1 if the customer has an Energy Orb but no A/C Switch.

$\ln(\frac{Peak\_\text{Price}}{OffPeak\_\text{Price}})_{it} xET\_ORB_i$: Interaction of ratio of peak to off-peak prices and ET_*ORB*
ET_*ORB*: is equal to 1 if the customer has an Energy Orb and A/C Switch.

$THI\_DIFF_t xD\_Month_k$: Interaction of THI_DIFF variable with monthly dummies.

$D\_TreatPeriod_t$: Dummy variable is equal to 1 when the period is June 2008 through September 30, 2008.

$D\_TreatPeriod_t xTreatCustomer_i$: Interaction of $D\_TreatPeriod_t$ with treatment customer dummy $TreatCustomer_i$

$TreatCustomer_i$: is equal to 1 for the treatment customers.

D_Month_k : Dummy variable that is equal to 1 when the month is k.

D_CPP_k : Dummy variable that is equal to 1 on the kth CPP day.

$D\_WEEKEND_t$: Dummy variable that is equal to 1 on weekends.

v_i : Time invariant fixed effects for customers.

u_{it} : Normally distributed error term.

It is important to note that this equation is estimated using data on both treatment and control customers before and during the pilot period. This type of database allows one to isolate the true impact of the experiment by controlling for any potential biases due to (i) differences between control and treatment customers in the pre-treatment period (ii) any changes in the consumption behavior of the treatment customers between the pre-treatment and treatment periods that are not related to the treatment per se. These potential confounding factors are controlled for by introducing dummy variables pertaining to the customer type and the analysis period. We also control for several other variables that are conjectured to affect the consumption choice between peak and off-peak periods.

This equation is estimated to determine the substitution elasticity of the BGE customers. *Substitution elasticity* indicates the percent change in the ratio of peak to off-peak consumption due to a one percent change in the ratio of peak to off-peak prices. Normally, if our model did not have any interactions of the price ratio with the weather term, (THI_DIFF), α_2 would represent the substitution elasticity estimated from this model. However, the specification of the BGE substitution model implied that the substitution elasticity of the BGE customers increased with the hotter weather. Therefore, we included an interaction term between the price ratio and the weather term in the model to capture this non-linearity in the elasticity term. Moreover, we also found that the substitution elasticities differ between customers with and without enabling technologies. We introduced the interaction terms between the price ratios and dummy variables for the enabling technologies to capture the incremental impact of these technologies on the price responsiveness of the customers. The estimation results for the substitution demand model are provided in Appendix 1, item 1.

It is important to note that the substitution elasticities for DPP, PTRL, and PTRH rates are found to be statistically indistinguishable from each other when tested separately in the estimation equation. This result has an important implication in that the SEP customers show the same responsiveness to dynamic pricing whether it is expressed as a price increase during critical hours or a peak time rebate.

Once the model is estimated and the parameters are identified, the substitution elasticities from can be derived using the following equations:

$$Subst\_Elasticity_{price} = \alpha_2 + \alpha_3 * THI\_DIFF_t \quad \text{(Price,Weather)} \qquad (1)$$

$$Subst\_Elasticity_{price+ORB} = \alpha_2 + \alpha_3 * THI\_DIFF_t + \alpha_4 \quad \text{(Price,Weather, and ORB)} \qquad (2)$$

$$Subst\_Elasticity_{price+ET\_ORB} = \alpha_2 + \alpha_3 * THI\_DIFF_t + \alpha_5 \quad \text{(Price,Weather, and ET\_ORB)} \qquad (3)$$

These equations make it possible to determine a substitution elasticity implied by a specific weather condition and the existence of an enabling technology.

Daily Demand Equation

The daily demand equation captures the change in the level of overall consumption due to the changes in the average daily price. Similar to the substitution equation, the daily equation also relies on the pre-treatment and the treatment period data on both treatment and control group customers. This practice allows the elasticity estimates to be free from biases concerning any pre-existing differences between the control and treatment group customers as well as the changes in the consumption patterns of the treatment customers between the pre-treatment and treatment periods due to factors other than the treatment. As in the case of substitution equations, we also control for other independent variables that can affect the average daily consumption and use the fixed effects routine to estimate the model. The specification of the daily demand model is provided below:

$$\ln(kWh)_{it} = \alpha_0 + \alpha_1 \ln(THI)_t + \alpha_2 \ln(Price)_{it} + \alpha_3 \ln(Price)_{it} x \ln(THI)_t + \sum_{k=1}^{6} \delta_k (\ln(THI)_t xD\_Month_k)$$
$$+ \alpha_4 D\_TreatPeriod_t + \alpha_5 D\_TreatPeriod_t xTreatCustomer_i + \sum_{k=1}^{6} \beta_k D\_Month_k + \sum_{k=1}^{12} \gamma_k D\_CPP_k$$
$$+ \alpha_6 D\_WEEKEND_t + v_i + u_{it}$$

where:

$\ln(kWh)_{it}$	: Logarithm of the daily average of the hourly load.
$\ln(THI)_{it}$	: Logarithm of the daily average of the hourly THI.
$\ln(Price)_{it}$	: Logarithm of the daily average of the hourly Price.
$\ln(Price)_{it} x \ln(THI)_{t}$	: Interaction of ln*(price)* with ln*(THI)*.
$\ln(THI)_{t} xD\_Month_{k}$	: Interaction of ln(*THI)* variable with monthly dummies.
$D\_TreatPeriod_{t}$	: Dummy variable is equal to 1 when the period is June 2008 through September 30, 2008.
$D\_TreatPeriod_{t} xTreatCustomer_{i}$	: Interaction of $D\_TreatPeriod_{t}$ with treatment customer dummy $TreatCustomer_{i}$.
	$TreatCustomer_{i}$: is equal to 1 for the treatment customers.
D_Month_{k}	: Dummy variable that is equal to 1 when the month is k.
D_CPP_{k}	: Dummy variable that is equal to 1 on the kth CPP day.
$D\_WEEKEND_{t}$	: Dummy variable that is equal to 1 on weekends.
v_{i}	: Time invariant fixed effects for customers.
u_{it}	: Normally distributed error term.

The daily equation is estimated to determine the daily price elasticity of the BGE customers. *Daily price elasticity* indicates the percent change in the daily average consumption due to a one percent change in the daily average price. Similar to the substitution elasticities, the daily price elasticities also increase with the warmer weather. In order to capture this non-linearity, we introduced an interaction term between the average daily price and the weather term (ln(THI)). Unlike the substitution elasticities, the daily elasticities did not differ between the customers with and without enabling technologies when empirically tested. For that reason, the model doesn't incorporate any interaction terms between the average daily price and the technology dummy variables. However, just like the substitution equation, the daily price elasticities from DPP, PTRL, and PTRH rates were not statistically distinguishable from each other when tested empirically. Therefore, there is a single price variable in the equation that incorporates the impacts of DPP, PTRL and PTRH rates. The estimation results for the daily demand equation are provided in Appendix 1, item 2.

The daily price elasticities from the estimated model can be derived using the following equation:

$$Daily\_Elasticity = \alpha_2 + \alpha_3 * \ln(THI)_t \tag{4}$$

It is possible to estimate a daily price elasticity implied by a specific weather condition using this equation.

3.B SUBSTITUTION AND DAILY PRICE ELASTICITIES

After estimating the parameters of the substitution and elasticity equations, we next calculate the substitution and daily price elasticities using the methodology described above. These elasticities are then used in the PRISM model to determine the impacts from the SEP pilot.

3.B.1 Period-Specific Elasticities

As mentioned earlier, the BGE price elasticities are weather dependent, *i.e.*, they take on different values for different weather conditions. The impact of weather on the substitution elasticity is captured through the THI_DIFF variable in Equation 1 and ln (THI) variable in Equation 4. In order to quantify the load impacts from the SEP pilot, we determined the "average CPP event day weather" to be used in the calculation of the price elasticities. We identified the average CPP event day weather by finding the average values of THI_DIFF and THI variables for the top ten hottest event days. Only 10 out of 12 were included in the averages, as the last two event days had very mild temperatures and were not representatives of the critical peak event days.[4] Table 3.1 presents the weather information for each of the 12 CPP event days as well as the average weather on top ten hottest days.

[4] These days nevertheless were included in the regression models since additional variability in the exogenous variables leads to greater precision in the parameter estimates.

Table 3.1: Weather Information on the CPP Event Days

ID	CPP Date	Minimum THI	Maximum THI	Average THI	ln(THI)	Average Peak THI	Average OffPeak THI	THI_DIFF
CPP Day 1	6/10/2008	70.15	83.75	77.06	4.34	83.33	75.41	7.92
CPP Day 2	6/27/2008	70.30	80.70	74.68	4.31	78.15	73.77	4.38
CPP Day 3	7/16/2008	63.60	78.00	71.94	4.28	77.26	70.54	6.72
CPP Day 4	7/17/2008	67.10	81.10	74.65	4.31	80.46	73.12	7.34
CPP Day 5	7/18/2008	69.20	81.30	76.07	4.33	80.47	74.91	5.55
CPP Day 6	7/22/2008	70.65	79.30	75.35	4.32	78.85	74.42	4.41
CPP Day 7	7/29/2008	68.45	78.60	73.55	4.30	78.15	72.31	5.81
CPP Day 8	8/19/2008	66.55	79.70	73.45	4.30	79.12	71.95	7.17
CPP Day 9	9/3/2008	62.45	79.30	71.73	**4.27**	78.77	69.88	**8.89**
CPP Day 10	9/4/2008	66.20	80.70	73.50	4.30	80.04	71.77	8.26
Average (CPP1-CPP10)	-	-	-	74.18	**4.31**	-	-	**6.65**
CPP Day 11	9/23/2008	60.30	67.65	64.41	**4.17**	66.71	63.80	**2.91**
CPP Day 12	9/30/2008	56.85	69.50	63.39	4.15	68.94	61.93	7.01

We also identified the CPP days with the mildest and the most extreme weather conditions using the difference between average peak and off-peak THI values, THI_DIFF. Accordingly, CPP Day 11 which fell on September 23, 2008 was the CPP day with the mildest weather (THI_DIFF= 2.91); whereas CPP Day 9 which fell on September 3, 2008 was the one with the most extreme weather (THI_DIFF=8.89).

Having identified the average, the mildest, and the most extreme CPP event day levels of the weather variable, we calculated the substitution and daily elasticities that correspond to these weather conditions. Table 3.2 presents the price elasticities implied by these weather terms.

Table 3.2: Substitution and Daily Price Elasticities Estimated from the SEP Pilot

Substitution / Daily	Type	Based on Mild Weather	Based on Average Weather	Based on Extreme Weather
Substitution Elasticity	Price Only	-0.073	-0.096	-0.109
Substitution Elasticity	Price + ORB	-0.113	-0.136	-0.149
Substitution Elasticity	Price + ET_ORB	-0.157	-0.180	-0.193
Daily Elasticity	-	-0.019	-0.039	-0.034

Although we estimated the price elasticities for the mildest and the most extreme CPP day weather conditions and calculated the load impacts implied by these elasticities, *we* *will focus on the elasticities and the impacts based on the average CPP day weather in the remainder of this report*. The price elasticities based on the average CPP day weather are the most appropriate to quantify the average load impacts from the SEP Pilot.

Using the average CPP day weather information, we find that the substitution elasticity from the DPP, PTRL, and PTRH rates alone as -0.096. This implies that a one percent change in the ratio of peak to off-peak prices leads to -0.096 percent change in the ratio of peak to off-peak consumption. When the DPP, PTRL, and PTRH rates are paired with the Energy Orb, the substitution elasticity becomes -0.136. Presence of both A/C switch and the Orb yields a substitution elasticity of -0.18. Accordingly, the substitution elasticity increases with the existence of enabling technologies as well as with the hotter weather, as can be seen in Table 3.2.

The daily price elasticity from DPP, PTRL, and PTRH rates is calculated as -0.039 using the average CPP day weather information. This implies that for one percent change in the average daily price, the average daily consumption changes by -0.039 percent. The daily price elasticity didn't vary with the presence of enabling technologies when tested empirically; therefore there is no technology variation in the daily price elasticities. However, similar to the substitution elasticities, the daily price elasticities increase with the hotter weather, as can be seen in Table 3.2.

3.B.2 Hour-Specific Elasticities

In the previous section, we estimated substitution elasticities that represent the rate of average load shifting behavior between peak and off-peak periods based on the ratio of average peak to off-peak prices. In addition to these *period-specific* substitution elasticities, we also estimated another set of substitution elasticities that are *hour-specific*. In this case, we estimated a separate substitution equation for each hour between 2 pm and 7 pm as well as two hours prior to the event and one hour after the event, that controls for the same parameters used to estimate the period-specific substitution elasticities.

We implement certain restrictions on the dataset to obtain the hour-specific substitution elasticities. For the peak hours, the dataset for each hourly substitution equation is restricted to the peak hour in question and all off-peak hours. For instance, if we are to estimate the substitution elasticity for hour 15, all the peak hours except hour 15 is dropped from the dataset. In this case, the dependent variable becomes "the ratio of load in hour 15 to the average load during off-peak hours" and the price variable becomes "the ratio of price in hour 15 to the average price during off-peak hours". In the same fashion, THI_DIFF becomes the difference between the THI variable in hour 15 and the average THI during off-peak hours.

For the off-peak hours, the dataset for each hourly substitution equation is restricted to the off-peak hour in question and all peak hours. For instance, if we are to estimate the substitution elasticity for hour 13, all the off-peak hours except hour 13 is dropped from the dataset. In this case, the dependent variable becomes "the ratio of average load during peak hours to the load in hour 13" and the price variable becomes "the ratio of the average price during peak hours to the price in hour 13". In the same fashion, THI_DIFF becomes the difference between the average THI during peak hours and the THI variable in hour 13.

It is important to note that the daily energy consumption equation is not re-estimated since it models daily energy use as a function of daily average price; not period or hour specific price. Estimation results for the hour-specific substitution equations are provided in Appendix 1, item 3.

After estimating hour-specific substitution equations, we calculated the hourly substitution elasticities based on the average CPP day hour-specific THI_DIFF values. Table 3.3 presents the hour-specific substitution elasticities.

Table 3.3: Hour-Specific Substitution Elasticities

Type	Hour 13	Hour 14	Hour 15	Hour 16	Hour 17	Hour 18	Hour 19	Hour 20
Price Only	-0.069	-0.051	-0.100	-0.112	-0.107	-0.094	-0.084	-0.070
Price + ORB	-0.100	-0.085	-0.139	-0.150	-0.144	-0.136	-0.131	-0.102
Price + ET_ORB	-0.160	-0.144	-0.180	-0.195	-0.186	-0.171	-0.158	-0.185

3.B.3 Impact of Socio-demographic Characteristics

Demand models allow one to determine the magnitude of price responsiveness that varies with the customer socio-demographic characteristics as well as the weather conditions. This can be achieved by introducing an interaction term between the price term and the relevant customer characteristics in the equation.

BGE conducted a survey to compile information on the characteristics of the SEP customers. This survey provided information on the appliances, housing characteristics, education levels, income levels and many other important characteristics of the SEP participants and the control group customers.

Using the information collected through this survey, we investigated the impacts of several socio-demographic characteristics on the elasticities estimated from the demand equations. We found that the ownership of central air conditioning did not statistically affect the substitution or daily price elasticities. Multi-family home residence reduced the substitution elasticity while having a college or above education level increased it. Owning a pool or having an income level above $75K increased the daily price elasticity. However, these results should be interpreted with some caution since not all customers responded to the surveys, and as a result we lost 20 percent of the analysis sample when estimating the demand equations with customer characteristics. For this reason, our impact evaluation is based on the demand equations without the socio-demographic variables.

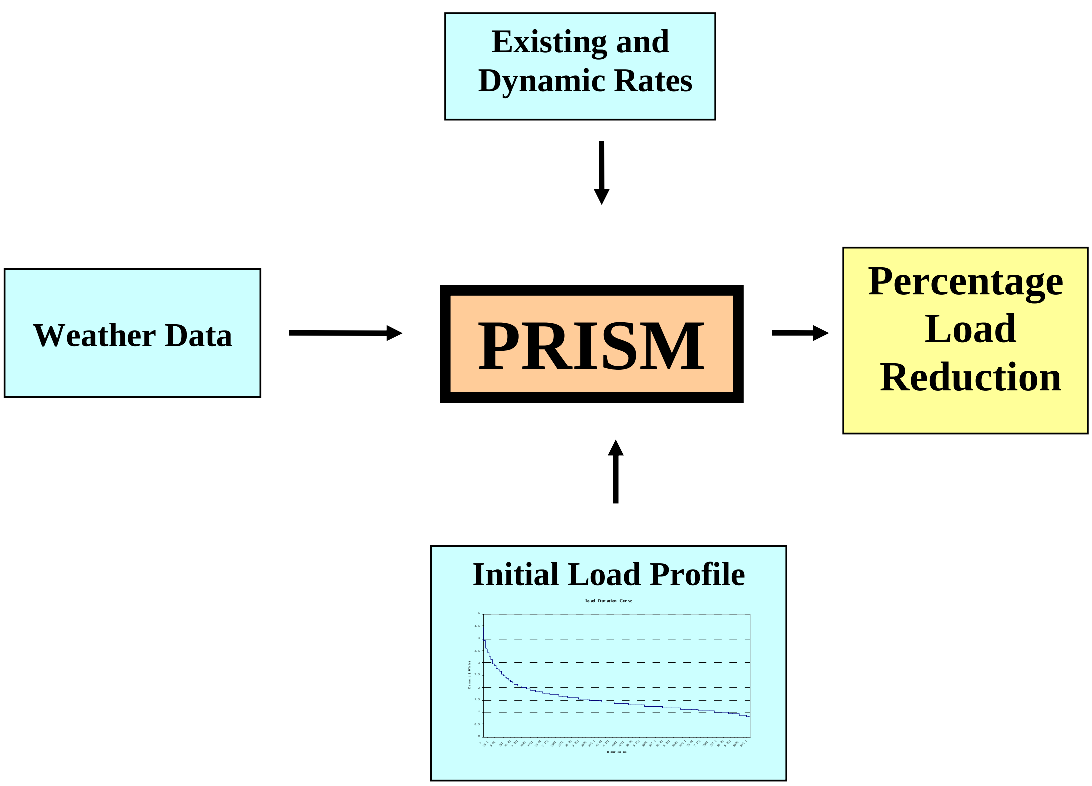
4. Load Impact Analysis Results

After estimating the substitution and daily demand equations, the next step in our impact evaluation study is to determine the load impacts from the rates tested in the SEP pilot.

We determined the impacts through the Pricing Impact Simulation Model (PRISM) software. The PRISM software emerged from the California Statewide Pricing Pilot (SPP). Although the PRISM was originally developed for California, it can be adapted to conditions in other parts of North America after adjustments have been made for weather, customer price responsiveness (price elasticities), rate, and load shape characteristics. We calibrated the PRISM model to the BGE conditions by updating the model with BGE's weather dependent price elasticity terms, standard BGE rates as well as the SEP rates and the average BGE customer load profile. The average BGE customer load profile was constructed by taking the average 2008 load profiles for residential non-heating (R) and residential heating (RH) customers weighted by their share in the population. RH customers represent one fourth of the BGE customer population whereas R customers represent the remaining three fourths.

Figure 4.1 shows the simplified structure of the PRISM Model.

Figure 4.1: PRISM Impacts Model- Inputs and Outputs



The PRISM model generates several metrics including percent change in peak and off-peak consumption on critical and non-critical days and percent change in total monthly consumption. These metrics are generated through solving the estimated substitution and daily demand equations. In this process, we plug in the standard rates, SEP rates, and the beginning load values in the estimated daily and substitution equations and solve for the new load values using the estimated elasticities. First, the new daily demand is solved using the daily price elasticities, and then this new level of daily demand is partitioned between peak and off-peak periods using the substitution elasticities. Table 4.1 presents the output from the PRISM model, in which the substitution and daily demand equations are solved for the PTRH with ET_ORB case. The generalized solution of these equations is provided in Appendix 2.

Table 4.1: PRISM Output- Solving for New Demand on Critical and Non-Critical Days

CPP Days			
	Peak Period	**Off Peak Period**	**Daily Period**
Current Critical Price ($/kWh)	$0.1533		$0.1533
New Critical Price ($/kWh)	$1.9033		$0.6550
Current Off-Peak Price		$0.1533	
New Off-Peak Price		$0.1533	
Price Elasticity	-0.1800		-0.0390
LN(Change in kWh per Hr)	-0.0298		
kWh per Hr per participant at old prices	2.70	1.77	1.96
kWh per Hr per participant at new prices	1.81	1.87	1.85
Delta kWh per participant	-0.89	0.10	-0.11
% Change in kWh per participant	**-32.95%**	**5.52%**	**-5.51%**

Non-CPP Days			
	Peak Period	**Off Peak Period**	**Daily Period**
Current Peak Price ($/kWh)	$0.1533		$0.1533
New Peak Price ($/kWh)	$0.1533		$0.1533
Current Off-Peak Price		$0.1533	
New Off-Peak Price		$0.1533	
Price Elasticity	-0.1800		-0.0390
LN(Change in kWh per Hr)	0.0869		
kWh per Hr per participant at old prices	1.63	1.49	1.52
kWh per Hr per participant at new prices	1.63	1.49	1.52
Delta kWh per participant	0.00	0.00	0.00
% Change in kWh per participant	**0.00%**	**0.00%**	**0.00%**

Next, we will discuss the load impacts from the SEP pilot calculated through the methodology described in the previous sections. As we estimated two sets of demand equations and price elasticities, *the period-specific* and *the hour-specific*, we will discuss the load impacts generated from these equations under different sections.

4.A PERIOD-SPECIFIC LOAD IMPACTS

After estimating the demand equations and calibrating the PRISM to BGE conditions, we calculate the load impacts associated with each of the programs tested in the SEP. In the following, we present the results for three different weather cases developed earlier, however we focus on the impacts "based on the average weather" since they represent the average impacts achieved throughout the pilot.

4.A.1 DPP Program Impacts

The DPP rates alone lead to 20.1 percent reduction in load during peak hours on critical peak days and 1.8 percent reduction in peak period load on non-critical days. When the rates are paired with the Energy Orb and the A/C switch technologies (ET_ORB), the peak period load reductions reach to 32.5 percent on critical days and 4.4 percent on non-critical days.

In addition to the peak period load impacts, the DPP rates also yield some total consumption impacts. Total monthly consumption increases by 0.9 percent with the DPP rates alone and by 1.2 percent when the DPP rates are paired with the ET_ORB technology combination. This is a result of the off-peak rates that are lower compared to the peak and the standard rates which give customers incentives to be less cautious about their consumption. Moreover, the off-peak hours represent a large percentage of the total hours during the pilot period.

Tables 4.2 presents the value of weather variables underlying the impact estimates that are shown in the following tables. Tables 4.3 and 4.4 present the impacts from the SEP DPP programs.

Table 4.2: Weather Variables Used in the Impact Simulations

Weather Variable	Mild Weather	Average Weather	Extreme Weather
THI_DIFF	2.91	6.65	8.89
Average THI	64.41	74.18	71.73
ln (THI)	4.17	4.31	4.27

Note: Average THI from the "average weather" case is higher than that from the "extreme weather" case. The reason is that weather scenarios are determined by the THI_DIFF variable, and average THI does not necessarily take the highest value when THI_DIFF takes the highest value.

Table 4.3: Load Impacts from DPP Rates

DPP			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-14.65%	**-20.11%**	-21.73%
Critical Days - Off-Peak (% of original consumption)	3.06%	2.36%	3.71%
Non-Critical Days - Peak (% of original consumption)	-1.68%	-1.76%	-2.33%
Non-Critical Days - Off-Peak (% of original consumption)	1.29%	2.17%	2.12%
Total Consumption Change (%/Month)	0.53%	**0.94%**	0.89%

Table 4.4: Load Impacts from DPP Rates paired with ET_ORB

DPP_ET_ORB			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-27.78%	**-32.54%**	-34.00%
Critical Days - Off-Peak (% of original consumption)	8.31%	7.36%	8.63%
Non-Critical Days - Peak (% of original consumption)	-4.30%	-4.38%	-4.93%
Non-Critical Days - Off-Peak (% of original consumption)	2.05%	2.92%	2.87%
Total Consumption Change (%/Month)	0.75%	**1.16%**	1.12%

4.A.2 PTRL Program Impacts

The PTRL rates alone yield an average peak load reduction of 17.8 percent on the critical peak days. When the PTRL rates are paired with the Energy Orb, the average load reduction reaches 23 percent. The presence of both the Energy Orb and the A/C switch lead to an average load reduction of 28.5 percent, on the critical peak days.
We do not observe load impacts on non-critical days as the SEP PTRL rates on these days are the same as the standard BGE rates.

PTRL rates yield some conservation during the SEP Pilot period. PTRL rates, regardless of the presence of the enabling technologies, lead to a 0.5 percent reduction in total monthly consumption. This implies that some of the load reductions in the peak period on critical days represented conservation rather than load shifting.

Tables 4.5 through 4.7 present the impacts from the SEP PTRL programs.

Table 4.5: Load Impacts from PTRL Rates

PTRL			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-12.74%	**-17.82%**	-19.09%
Critical Days - Off-Peak (% of original consumption)	2.07%	1.00%	2.26%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.24%	**-0.50%**	-0.43%

Table 4.6: Load Impacts from PTRL Rates paired with ORB

PTRL_ORB			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-18.21%	**-23.03%**	-24.25%
Critical Days - Off-Peak (% of original consumption)	4.26%	3.09%	4.33%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.24%	**-0.50%**	-0.43%

Table 4.7: Load Impacts from PTRL Rates paired with ET_ORB

PTRL_ET_ORB			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-23.95%	**-28.48%**	-29.65%
Critical Days - Off-Peak (% of original consumption)	6.55%	5.28%	6.49%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.24%	**-0.50%**	-0.43%

4.A.3 PTRH Programs Impacts

The PTRH rates alone yield an average peak load reduction of 21 percent on the critical peak days. When the PTRH rates are paired with the Energy Orb, the average load reduction reaches 27 percent. The presence of both the Energy Orb and the A/C switch lead to an average load reduction of 33 percent, on the critical peak days.

We do not observe load impacts on non-critical days as the SEP PTRH rates on these days are the same as the standard BGE rates.

PTRH rates yield some conservation during the SEP Pilot period. PTRH rates, regardless of the presence of the enabling technologies, lead to a 0.6 percent reduction in total monthly consumption. This implies that some of the load reductions in the peak period on critical days represented conservation rather than load shifting. Tables 4.8 through 4.10 present the impacts from the SEP PTRH programs.

Table 4.8: Load Impacts from PTRH Rates

PTRH			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-14.98%	**-20.94%**	-22.34%
Critical Days - Off-Peak (% of original consumption)	2.19%	0.69%	2.20%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.31%	**-0.63%**	-0.54%

Table 4.9: Load Impacts from PTRH Rates paired with ORB

PTRH_ORB			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-21.24%	**-26.83%**	-28.18%
Critical Days - Off-Peak (% of original consumption)	4.70%	3.06%	4.54%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.31%	**-0.63%**	-0.54%

Table 4.10: Load Impacts from PTRH Rates paired with ET_ORB

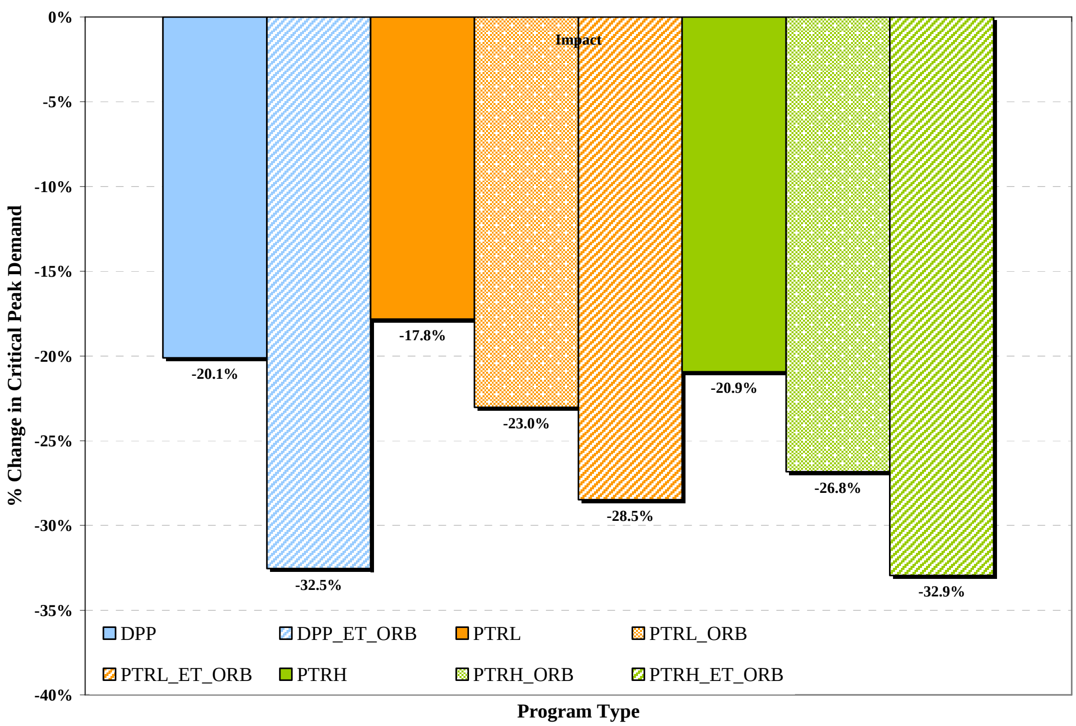
PTRH_ET_ORB			
Impact Type	**Based on Mild Weather**	**Based on Average Weather**	**Based on Extreme Weather**
Critical Days - Peak (% of original consumption)	-27.75%	**-32.95%**	-34.22%
Critical Days - Off-Peak (% of original consumption)	7.30%	5.52%	6.96%
Non-Critical Days - Peak (% of original consumption)	0.00%	0.00%	0.00%
Non-Critical Days - Off-Peak (% of original consumption)	0.00%	0.00%	0.00%
Total Consumption Change (%/Month)	-0.31%	**-0.63%**	-0.54%

4.A.4 Summary of the SEP Load Impacts

Average reduction in critical peak period usage ranges from 18 to 33 percent from the DPP, PTRL and PTRH rates and the technology combinations tested in the SEP Pilot. The programs without the enabling technologies yield impacts in the range of 18 to 21 percent. The presence of the Energy Orb conclusively increases the demand response raising the range of impacts to 23 to 27 percent. The presence of both A/C switch and the Energy Orb substantially increases the impacts achieved from the rates alone and yields impacts in the range of 28 to 33 percent. As a result of the programs, total monthly consumption increases by roughly one percent for DPP and decreases by about half percent for PTRL and 0.6 percent for PTRH.

Figure 4.2 presents the average peak load impacts on critical peak days across the SEP programs.

Figure 4.2: The SEP Pilot Demand Response Impact Summary



4.B HOUR-SPECIFIC LOAD IMPACTS

In addition to estimating the period-specific load impacts that are averaged over the peak and off-peak periods, we also estimated the load impacts that are attributable to each hour between 2 pm and 7 pm as well as two hours prior to the event and one hour after the event.

The percentage load impact calculation methodology remains the same as before, except that the period-specific elasticities are now replaced with the hour specific elasticities. After estimating hour-specific percentage load impacts, we apply these percentages on hourly load levels without any demand response to calculate "kWh per hour reduction" for all hours of interest.

We estimate the hourly load levels before demand response (base load) for a series of THI values. In other words, using the average BGE customer load profile, we estimate what the load level would be for a given hour and a THI value on a CPP day before any demand response.

In order to estimate the load reduction in kWh per hour terms for different THI values, we first need to estimate what the load before demand response (base load) would be for a given hour and for a given THI. To obtain hourly base load values for different THI values, we estimate hour by hour equations between load and the THI values for all hours of interest on 12 CPP days using the average BGE customer load profile. The results of these estimations can be found in Appendix 1, item 4.

Using the parameters of these equations, we obtain the hourly base load values that correspond to given THI values as presented in Table 4.11.

Table 4.11: Estimated Base Load Values Before Demand Response (kWh/ hour)

Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	2.96	2.91	2.85	2.80	2.74	2.69	2.64	2.58	2.53	2.48	2.42	2.37	2.32	2.26
Hour 14	3.17	3.11	3.05	2.99	2.93	2.87	2.81	2.75	2.69	2.63	2.57	2.51	2.44	2.38
Hour 15	3.16	3.10	3.04	2.98	2.92	2.86	2.80	2.74	2.68	2.62	2.56	2.50	2.44	2.38
Hour 16	3.35	3.28	3.21	3.15	3.08	3.02	2.95	2.88	2.82	2.75	2.68	2.62	2.55	2.48
Hour 17	3.52	3.46	3.39	3.32	3.26	3.19	3.12	3.06	2.99	2.92	2.86	2.79	2.72	2.66
Hour 18	3.66	3.59	3.53	3.46	3.40	3.33	3.26	3.20	3.13	3.07	3.00	2.93	2.87	2.80
Hour 19	3.46	3.41	3.36	3.30	3.25	3.20	3.15	3.10	3.05	3.00	2.94	2.89	2.84	2.79
Hour 20	3.55	3.51	3.46	3.41	3.36	3.31	3.26	3.21	3.17	3.12	3.07	3.02	2.97	2.92

We next calibrate the PRISM model with the hourly elasticities, and obtain the percentage load impacts from PTRL programs which are presented in Table 4.12.

Table 4.12: Load Impacts from the PTRL Programs (%)

PTRL	% IMPACT													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	-1.7%	-1.6%	-1.5%	-1.4%	-1.3%	-1.3%	-1.2%	-1.1%	-1.0%	-0.9%	-0.8%	-0.8%	-0.7%	-0.6%
Hour 14	-3.3%	-3.2%	-3.0%	-2.9%	-2.8%	-2.6%	-2.5%	-2.3%	-2.2%	-2.0%	-1.9%	-1.8%	-1.6%	-1.5%
Hour 15	-24.3%	-23.8%	-23.3%	-22.8%	-22.3%	-21.8%	-21.3%	-20.8%	-20.2%	-19.7%	-19.2%	-18.7%	-18.1%	-17.6%
Hour 16	-25.6%	-25.1%	-24.6%	-24.1%	-23.6%	-23.1%	-22.6%	-22.0%	-21.5%	-21.0%	-20.5%	-20.0%	-19.5%	-18.9%
Hour 17	-24.5%	-24.1%	-23.6%	-23.2%	-22.7%	-22.3%	-21.8%	-21.4%	-20.9%	-20.5%	-20.0%	-19.6%	-19.1%	-18.6%
Hour 18	-22.3%	-21.9%	-21.5%	-21.1%	-20.7%	-20.3%	-19.9%	-19.5%	-19.1%	-18.7%	-18.4%	-18.0%	-17.6%	-17.2%
Hour 19	-19.9%	-19.6%	-19.4%	-19.1%	-18.8%	-18.6%	-18.3%	-18.0%	-17.8%	-17.5%	-17.2%	-17.0%	-16.7%	-16.4%
Hour 20	0.5%	0.5%	0.4%	0.4%	0.3%	0.3%	0.2%	0.2%	0.1%	0.0%	0.0%	-0.1%	-0.1%	-0.2%

PTRL_ORB	% IMPACT													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	0.0%	0.1%	0.2%	0.3%	0.4%	0.4%	0.5%	0.6%	0.7%	0.8%	0.9%	0.9%	1.0%	1.1%
Hour 14	-1.4%	-1.3%	-1.1%	-1.0%	-0.8%	-0.7%	-0.6%	-0.4%	-0.3%	-0.2%	0.0%	0.1%	0.3%	0.4%
Hour 15	-29.1%	-28.6%	-28.2%	-27.7%	-27.2%	-26.7%	-26.2%	-25.7%	-25.2%	-24.7%	-24.2%	-23.7%	-23.2%	-22.7%
Hour 16	-30.2%	-29.7%	-29.2%	-28.8%	-28.3%	-27.8%	-27.3%	-26.8%	-26.3%	-25.8%	-25.3%	-24.8%	-24.3%	-23.8%
Hour 17	-29.0%	-28.6%	-28.2%	-27.8%	-27.3%	-26.9%	-26.5%	-26.1%	-25.6%	-25.2%	-24.8%	-24.3%	-23.9%	-23.4%
Hour 18	-27.5%	-27.1%	-26.8%	-26.4%	-26.0%	-25.7%	-25.3%	-24.9%	-24.5%	-24.2%	-23.8%	-23.4%	-23.0%	-22.6%
Hour 19	-25.9%	-25.6%	-25.4%	-25.1%	-24.9%	-24.6%	-24.4%	-24.1%	-23.9%	-23.6%	-23.4%	-23.1%	-22.9%	-22.6%
Hour 20	2.2%	2.2%	2.1%	2.1%	2.0%	2.0%	1.9%	1.9%	1.8%	1.8%	1.7%	1.7%	1.6%	1.5%

PTRL_ET_ORB	% IMPACT													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	3.2%	3.3%	3.4%	3.4%	3.5%	3.6%	3.7%	3.7%	3.8%	3.9%	4.0%	4.0%	4.1%	4.2%
Hour 14	1.8%	1.9%	2.1%	2.2%	2.3%	2.5%	2.6%	2.7%	2.8%	3.0%	3.1%	3.2%	3.4%	3.5%
Hour 15	-33.9%	-33.5%	-33.0%	-32.5%	-32.1%	-31.6%	-31.1%	-30.7%	-30.2%	-29.7%	-29.2%	-28.8%	-28.3%	-27.8%
Hour 16	-35.4%	-34.9%	-34.5%	-34.0%	-33.6%	-33.1%	-32.7%	-32.2%	-31.7%	-31.3%	-30.8%	-30.3%	-29.8%	-29.4%
Hour 17	-34.0%	-33.6%	-33.2%	-32.7%	-32.3%	-31.9%	-31.5%	-31.1%	-30.7%	-30.3%	-29.9%	-29.5%	-29.0%	-28.6%
Hour 18	-31.7%	-31.3%	-31.0%	-30.6%	-30.3%	-29.9%	-29.6%	-29.2%	-28.8%	-28.5%	-28.1%	-27.8%	-27.4%	-27.0%
Hour 19	-29.2%	-28.9%	-28.7%	-28.4%	-28.2%	-28.0%	-27.7%	-27.5%	-27.2%	-27.0%	-26.7%	-26.5%	-26.2%	-26.0%
Hour 20	6.4%	6.3%	6.3%	6.2%	6.2%	6.1%	6.1%	6.0%	6.0%	5.9%	5.9%	5.8%	5.8%	5.7%

After calculating the percentage load impacts through PRISM, we applied these percentages on the base load values that are presented in Table 4.11. Resulting load impacts (in terms of kWh per hour) are provided in Table 4.13.

Table 4.13: Load Impacts from the PTRL Programs (kWh/hour)

PTRL	LOAD IMPACT (kWh/Hour)													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.01
Hour 14	0.11	0.10	0.09	0.09	0.08	0.08	0.07	0.06	0.06	0.05	0.05	0.04	0.04	0.04
Hour 15	0.77	0.74	0.71	0.68	0.65	0.62	0.60	0.57	0.54	0.52	0.49	0.47	0.44	0.42
Hour 16	0.86	0.82	0.79	0.76	0.73	0.70	0.67	0.64	0.61	0.58	0.55	0.52	0.50	0.47
Hour 17	0.86	0.83	0.80	0.77	0.74	0.71	0.68	0.65	0.63	0.60	0.57	0.55	0.52	0.50
Hour 18	0.81	0.79	0.76	0.73	0.70	0.68	0.65	0.62	0.60	0.57	0.55	0.53	0.50	0.48
Hour 19	0.69	0.67	0.65	0.63	0.61	0.59	0.58	0.56	0.54	0.52	0.51	0.49	0.47	0.46
Hour 20	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01

PTRL_ORB	LOAD IMPACT (kWh/Hour)													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
Hour 14	0.04	0.04	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.00	0.00	0.00	-0.01	-0.01
Hour 15	0.92	0.89	0.86	0.83	0.79	0.76	0.73	0.71	0.68	0.65	0.62	0.59	0.57	0.54
Hour 16	1.01	0.98	0.94	0.91	0.87	0.84	0.81	0.77	0.74	0.71	0.68	0.65	0.62	0.59
Hour 17	1.02	0.99	0.96	0.92	0.89	0.86	0.83	0.80	0.77	0.74	0.71	0.68	0.65	0.62
Hour 18	1.01	0.98	0.94	0.91	0.88	0.85	0.83	0.80	0.77	0.74	0.71	0.69	0.66	0.63
Hour 19	0.89	0.87	0.85	0.83	0.81	0.79	0.77	0.75	0.73	0.71	0.69	0.67	0.65	0.63
Hour 20	-0.08	-0.08	-0.07	-0.07	-0.07	-0.07	-0.06	-0.06	-0.06	-0.05	-0.05	-0.05	-0.05	-0.05

PTRL_ET_ORB	LOAD IMPACT (kWh/Hour)													
Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	-0.09	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.09
Hour 14	-0.06	-0.06	-0.06	-0.07	-0.07	-0.07	-0.07	-0.07	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08
Hour 15	1.07	1.04	1.00	0.97	0.94	0.90	0.87	0.84	0.81	0.78	0.75	0.72	0.69	0.66
Hour 16	1.18	1.15	1.11	1.07	1.03	1.00	0.96	0.93	0.89	0.86	0.83	0.79	0.76	0.73
Hour 17	1.20	1.16	1.12	1.09	1.05	1.02	0.98	0.95	0.92	0.89	0.85	0.82	0.79	0.76
Hour 18	1.16	1.13	1.09	1.06	1.03	1.00	0.96	0.93	0.90	0.87	0.84	0.81	0.79	0.76
Hour 19	1.01	0.99	0.96	0.94	0.92	0.89	0.87	0.85	0.83	0.81	0.79	0.77	0.75	0.72
Hour 20	-0.23	-0.22	-0.22	-0.21	-0.21	-0.20	-0.20	-0.19	-0.19	-0.18	-0.18	-0.18	-0.17	-0.17

Tables 4.14 and 4.15 present the similar information for the PTRH programs.

Table 4.14: Load Impacts from the PTRH Programs (%)

PTRH	% IMPACT													
	THI													
Hour Ending	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	-2.4%	-2.3%	-2.2%	-2.1%	-2.0%	-1.9%	-1.8%	-1.7%	-1.6%	-1.5%	-1.4%	-1.3%	-1.2%	-1.1%
Hour 14	-4.3%	-4.1%	-3.9%	-3.8%	-3.6%	-3.4%	-3.3%	-3.1%	-3.0%	-2.8%	-2.6%	-2.5%	-2.3%	-2.1%
Hour 15	-28.3%	-27.7%	-27.2%	-26.6%	-26.0%	-25.4%	-24.9%	-24.3%	-23.7%	-23.1%	-22.5%	-21.9%	-21.3%	-20.7%
Hour 16	-29.7%	-29.1%	-28.6%	-28.0%	-27.5%	-26.9%	-26.3%	-25.7%	-25.1%	-24.6%	-24.0%	-23.4%	-22.8%	-22.2%
Hour 17	-28.5%	-28.0%	-27.5%	-27.0%	-26.5%	-26.0%	-25.5%	-25.0%	-24.5%	-23.9%	-23.4%	-22.9%	-22.4%	-21.9%
Hour 18	-26.0%	-25.5%	-25.1%	-24.7%	-24.2%	-23.8%	-23.3%	-22.9%	-22.4%	-22.0%	-21.5%	-21.1%	-20.6%	-20.2%
Hour 19	-23.3%	-23.0%	-22.7%	-22.4%	-22.1%	-21.8%	-21.5%	-21.2%	-20.9%	-20.6%	-20.3%	-20.0%	-19.7%	-19.4%
Hour 20	0.2%	0.1%	0.0%	0.0%	-0.1%	-0.1%	-0.2%	-0.3%	-0.3%	-0.4%	-0.4%	-0.5%	-0.6%	-0.6%

PTRH_ORB	% IMPACT													
	THI													
Hour Ending	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	-0.4%	-0.3%	-0.2%	-0.1%	0.0%	0.1%	0.2%	0.3%	0.3%	0.4%	0.5%	0.6%	0.7%	0.8%
Hour 14	-2.0%	-1.9%	-1.7%	-1.6%	-1.4%	-1.2%	-1.1%	-0.9%	-0.8%	-0.6%	-0.5%	-0.3%	-0.1%	0.0%
Hour 15	-33.7%	-33.1%	-32.6%	-32.0%	-31.5%	-31.0%	-30.4%	-29.8%	-29.3%	-28.7%	-28.2%	-27.6%	-27.0%	-26.4%
Hour 16	-34.9%	-34.3%	-33.8%	-33.3%	-32.7%	-32.2%	-31.6%	-31.1%	-30.5%	-30.0%	-29.4%	-28.9%	-28.3%	-27.7%
Hour 17	-33.6%	-33.1%	-32.6%	-32.2%	-31.7%	-31.2%	-30.7%	-30.2%	-29.8%	-29.3%	-28.8%	-28.3%	-27.8%	-27.3%
Hour 18	-31.9%	-31.5%	-31.0%	-30.6%	-30.2%	-29.8%	-29.4%	-29.0%	-28.5%	-28.1%	-27.7%	-27.3%	-26.8%	-26.4%
Hour 19	-30.0%	-29.7%	-29.5%	-29.2%	-28.9%	-28.6%	-28.3%	-28.1%	-27.8%	-27.5%	-27.2%	-26.9%	-26.6%	-26.3%
Hour 20	2.1%	2.0%	2.0%	1.9%	1.9%	1.8%	1.7%	1.7%	1.6%	1.6%	1.5%	1.4%	1.4%	1.3%

PTRH_ET_ORB	% IMPACT													
	THI													
Hour Ending	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	3.2%	3.3%	3.4%	3.5%	3.5%	3.6%	3.7%	3.8%	3.9%	4.0%	4.1%	4.1%	4.2%	4.3%
Hour 14	1.6%	1.8%	1.9%	2.1%	2.2%	2.4%	2.5%	2.6%	2.8%	2.9%	3.1%	3.2%	3.4%	3.5%
Hour 15	-39.0%	-38.5%	-38.0%	-37.4%	-36.9%	-36.4%	-35.9%	-35.4%	-34.9%	-34.3%	-33.8%	-33.3%	-32.7%	-32.2%
Hour 16	-40.6%	-40.1%	-39.6%	-39.1%	-38.6%	-38.1%	-37.6%	-37.1%	-36.5%	-36.0%	-35.5%	-35.0%	-34.5%	-33.9%
Hour 17	-39.0%	-38.6%	-38.1%	-37.7%	-37.2%	-36.8%	-36.3%	-35.9%	-35.4%	-35.0%	-34.5%	-34.0%	-33.6%	-33.1%
Hour 18	-36.5%	-36.1%	-35.7%	-35.3%	-34.9%	-34.5%	-34.1%	-33.7%	-33.3%	-32.9%	-32.5%	-32.1%	-31.7%	-31.3%
Hour 19	-33.7%	-33.4%	-33.2%	-32.9%	-32.6%	-32.4%	-32.1%	-31.8%	-31.5%	-31.3%	-31.0%	-30.7%	-30.4%	-30.2%
Hour 20	6.7%	6.7%	6.6%	6.6%	6.5%	6.5%	6.4%	6.4%	6.3%	6.2%	6.2%	6.1%	6.1%	6.0%

Table 4.15: Load Impacts from the PTRH Programs (kWh/hour)

PTRH — LOAD IMPACT (kWh/Hour)

Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	0.07	0.07	0.06	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.03	0.03
Hour 14	0.14	0.13	0.12	0.11	0.11	0.10	0.09	0.09	0.08	0.07	0.07	0.06	0.06	0.05
Hour 15	0.90	0.86	0.83	0.79	0.76	0.73	0.70	0.67	0.64	0.61	0.58	0.55	0.52	0.49
Hour 16	0.99	0.96	0.92	0.88	0.85	0.81	0.78	0.74	0.71	0.68	0.64	0.61	0.58	0.55
Hour 17	1.00	0.97	0.93	0.90	0.86	0.83	0.80	0.76	0.73	0.70	0.67	0.64	0.61	0.58
Hour 18	0.95	0.92	0.88	0.85	0.82	0.79	0.76	0.73	0.70	0.67	0.65	0.62	0.59	0.56
Hour 19	0.80	0.78	0.76	0.74	0.72	0.70	0.68	0.66	0.64	0.62	0.60	0.58	0.56	0.54
Hour 20	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02

PTRH_ORB — LOAD IMPACT (kWh/Hour)

Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	0.01	0.01	0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02
Hour 14	0.06	0.06	0.05	0.05	0.04	0.04	0.03	0.03	0.02	0.02	0.01	0.01	0.00	0.00
Hour 15	1.06	1.03	0.99	0.96	0.92	0.89	0.85	0.82	0.79	0.75	0.72	0.69	0.66	0.63
Hour 16	1.17	1.13	1.09	1.05	1.01	0.97	0.93	0.90	0.86	0.82	0.79	0.76	0.72	0.69
Hour 17	1.18	1.14	1.11	1.07	1.03	1.00	0.96	0.92	0.89	0.86	0.82	0.79	0.76	0.72
Hour 18	1.17	1.13	1.09	1.06	1.03	0.99	0.96	0.93	0.89	0.86	0.83	0.80	0.77	0.74
Hour 19	1.04	1.01	0.99	0.96	0.94	0.92	0.89	0.87	0.85	0.82	0.80	0.78	0.76	0.73
Hour 20	-0.07	-0.07	-0.07	-0.07	-0.06	-0.06	-0.06	-0.05	-0.05	-0.05	-0.05	-0.04	-0.04	-0.04

PTRH_ET_ORB — LOAD IMPACT (kWh/Hour)

Hour Ending	THI													
	85.5	85.0	84.5	84.0	83.5	83.0	82.5	82.0	81.5	81.0	80.5	80.0	79.5	79.0
Hour 13	-0.09	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10
Hour 14	-0.05	-0.05	-0.06	-0.06	-0.06	-0.07	-0.07	-0.07	-0.08	-0.08	-0.08	-0.08	-0.08	-0.08
Hour 15	1.23	1.19	1.16	1.12	1.08	1.04	1.01	0.97	0.94	0.90	0.87	0.83	0.80	0.77
Hour 16	1.36	1.32	1.27	1.23	1.19	1.15	1.11	1.07	1.03	0.99	0.95	0.92	0.88	0.84
Hour 17	1.37	1.33	1.29	1.25	1.21	1.17	1.13	1.10	1.06	1.02	0.99	0.95	0.91	0.88
Hour 18	1.34	1.30	1.26	1.22	1.19	1.15	1.11	1.08	1.04	1.01	0.98	0.94	0.91	0.88
Hour 19	1.17	1.14	1.11	1.09	1.06	1.04	1.01	0.99	0.96	0.94	0.91	0.89	0.86	0.84
Hour 20	-0.24	-0.23	-0.23	-0.22	-0.22	-0.21	-0.21	-0.20	-0.20	-0.19	-0.19	-0.19	-0.18	-0.18