2013-2014 Retail Demand Response and Dynamic Pricing Project

Final Report

To:

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Public Version

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Executive Summary

This report provides estimates of the amount of demand response that is occurring outside of ERCOT's formal markets for energy and ancillary services and outside of ERCOT's Emergency Response Service (ERS) program. This analysis is based on data collected through a survey of load-serving entities (LSEs) -- including Retail Electric Providers (REPs), municipal electric systems, and rural electric cooperatives serving the ERCOT power region.

Demand Response to 4CP Events

During one of the four summer coincident peak (4CP) intervals used to recover transmission costs from consumers with interval data recorders (IDRs) and LSEs, we estimate about 500 MW of demand reduction. About half of this response is from energy consumers served at transmission voltage in areas opened to retail competition. A similar amount of demand reduction may be traced to programs operated by non-opt-in entities (NOIEs). The demand reduction achieved through the NOIE programs varies considerably during different events and we have been unable to independently verify the impacts reports by the NOIEs. So we are using a "round number" to report the impacts of the NOIE programs here.

Table ES.1: Estimated Average Demand Response During a 4CP in 2013

	Total MW
Demand Response from Energy Consumers Served at Transmission Voltage in Competitive Areas (regardless of their participation in formal programs) (1)	250
Programs Implemented by NOIEs (2)	200
Other Load Control Programs activated during a CP	Small
Real Time Pricing (RTP) and Block and Index (BI) Programs (incidental impacts during a CP)	Small
Rough Estimate of Other Response not otherwise accounted for (3)	50
TOTAL	500
Notes:	
(1) An historical baseline calculation yields an average estimate of 251 MW for the four CPs in 2013. Regression analysis suggests a reduction of 201 MW on average over the past 5 years.	
(2) Based on a review of savings estimates reported by NOIEs. We have been unsuccessful in independently confirming these estimates.	
(3) This is a conservative estimate based on judgment, to account for response by industrials with IDRs served at a voltage other than transmission and industrials within NOIE service areas.	

There is some "Other Response" that is similarly difficult to independently verify with the data available to us. Yet, we know anecdotally that it exists. This might include response by large industrial energy consumers served by NOIEs and the response of energy consumers with IDRs served at a voltage other than transmission. With only aggregate NOIE-level data or aggregate consumption for consumers served at primary voltage to us, we were unable to detect this response. Our conservative estimate of 50 MW is based on judgment.

One REP-sponsored Other Load Control program was deployed during one of the CPs in 2013, but the impact of this 15-minute deployment which overlapped part of the interval setting the CP was difficult to detect.

About three-quarters of the demand reduction during 4CPs is coming from larger commercial, industrial, and institutional consumers. The source of the other one-quarter is from the residential sector, as noted in Figure ES.1. This estimate was informed by a review of the composition of participants in the NOIE programs.

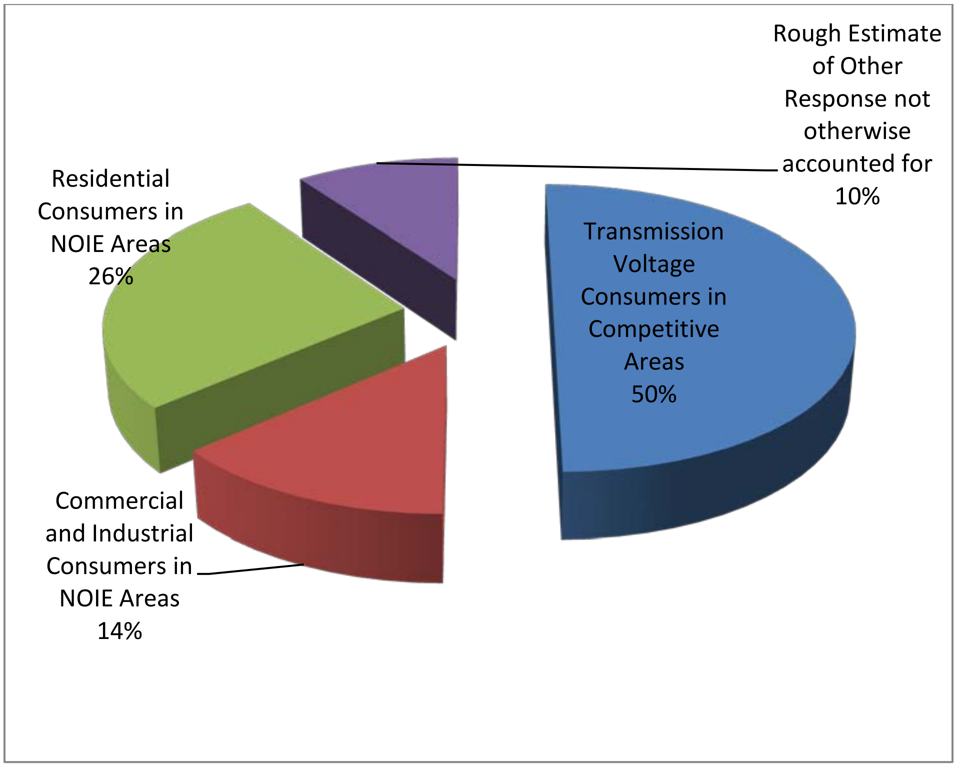


Figure ES.1: Composition of Demand Response during a 4CP by Source

We note that our estimate of about 500 MW is lower than the estimates of demand response during 4CPs that ERCOT had earlier estimated.[1] Consequently, we conducted discussions with the ERCOT staff to identify the differences, and the ERCOT staff conducted some supplemental analysis.

Demand Response to Spikes in Wholesale Prices

The demand reduction in response to price spikes in 2013 was around 432.5 MW, as shown in Table ES.2. Most of this came from larger commercial and industrial energy consumers served through real-time pricing programs and block and index programs. The load control programs of the NOIEs can have a large impact, as well.

[1] Calvin Opheim, *Load Forecasting Process Review*, presentation to the Generation Adequacy Task Force, October 7, 2013, slide 14.

Table ES.2: **Estimated Demand Response During a Spike in Wholesale Energy Prices in 2013 (1)**

(Load Zone Settlement Point Price above $3,000/MWh)	
	Total MW
RTP and BI Programs	
Customers with IDR Meters	180
Customers with AMS Meters	2
Rough Estimate of Other Response not otherwise accounted for (2)	50
Load Control Programs Implemented by NOIEs	200
Peak Load Rebate Programs (3)	0.5
TOTAL	432.5
Notes:	
(1) There were very few price spikes in ERCOT in 2013. Consequently, many programs were not activated and the estimates here do not reflect potential demand reduction. Methodology: Regression analysis.	
(2) This is a conservative estimate based on judgment, to account for response by industrials with IDRs served at a voltage other than transmission and industrials within NOIE service areas.	
(3) A discussion of the data and calculations used to derive our estimate of the demand reduction from Peak Load Rebate Programs has been removed from this "public" report, in order to protect confidential information from disclosure.	

We detected a strong increase in demand reduction as wholesale market prices increase, as noted in Figure ES.2.

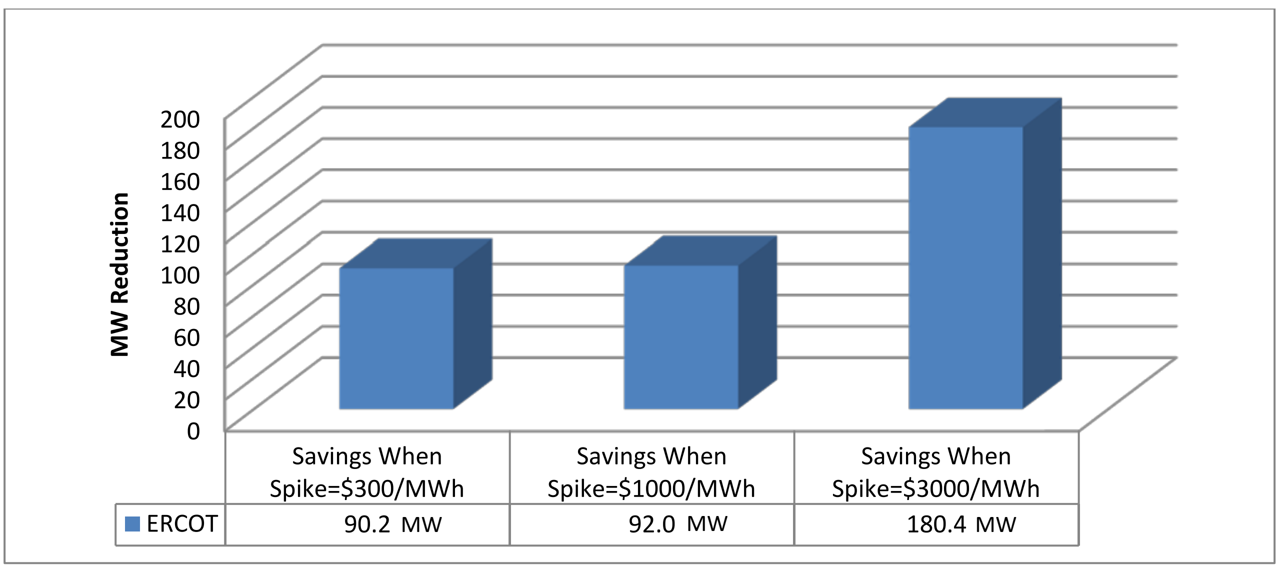


Figure ES.2: Demand Response by Consumers with IDRs Increase as the Wholesale Market Price Increases

Chapter 1: Introduction

A better understanding of demand response (DR) is important to maintaining reliability in the Electric Reliability Council of Texas (ERCOT) power market in light of ERCOT's "energy-only" market design which relies extensively on market forces to balance supply and demand. While the amount of curtailable or interruptible load participating in ERCOT's formal markets and the Emergency Response Service program is well-known to ERCOT's system operators and planners, the amount of demand response that is occurring outside of formal markets in response to a spike in wholesale prices or a program implemented by a load-serving entity (LSEs) is not well-understood. Deployments of such "out-of-market DR" [2] are generally not reported to ERCOT in advance or in real-time.

Using its authority under Public Utility Commission of Texas (PUCT) Substantive Rule §25.505(e)(5), ERCOT has periodically surveyed LSEs to determine the magnitude of out-of-market DR activities. This report summarizes the results obtained through the survey conducted by ERCOT during the summer of 2013.

The types of DR products for which data were collected include:

- Time of Use (TOU) pricing
- Critical Peak pricing/rebates
- Real-Time pricing
- Direct Load Control
- Programs designed to facilitate response to Four Coincident Peak (4CP) transmission charges

As a component of ERCOT's survey, Retail Electric Providers (REPs) serving energy consumers in the areas of ERCOT opened to retail competition were asked to provide the ESI IDs or account numbers of consumers participating in a REP-sponsored out-of-market DR program during the summer of 2013. This report provides an independent quantification of the customer-specific response to various REP-initiated deployments.

While REPs were asked to identify the consumers participating in time-of-use pricing (TOU) programs such as "Free Weekends" and "Free Nights" programs, it was decided that the analysis described in this report would focus on "event-driven" DR. Nonetheless, we have included data summarizing the popularity of TOU programs during the summer of 2013 in this report, albeit without any quantification of the change in load patterns resulting from such programs.

Information was also collected pertaining to DR programs offered by non-opt-in entities (NOIEs, which tend to be municipal utility systems and rural electric cooperative utilities which have not opted-in to retail competition). However, since the Smart Meter Texas (SMT) repository of interval-level usage information does not include data for consumers in the NOIE areas, no independent analysis was conducted to quantify the impacts from the NOIE programs.

[2] The California Public Utilities Commission and the Midcontinent Independent System Operator (MISO) have adopted the term "Load Modifying Resource Demand Response" to describe demand response programs which are not directly dispatched by an ISO.

Table 1.1 summarizes the numbers of REPs reporting programs and the number of programs provided by these REPs under various categories.

Table 1.1: Programs by REPs - Summary Table[3]

	REP1	REP2	REP5	REP6	REP7	REP8
OLC	11	4	--	--	--	--
RTP	--	--	4	--	--	--
PR	--	4	--	--	--	--
BI	--	--	1	4	--	--
4CP	--	--	--	--	4	4
OTHER	--	--	4	--	--	--

Where:

- OLC = Other Load Control
- RTP = Real-Time Pricing
- PR = Peak Rebate
- BI = Block & Index pricing
- 4CP = REP-initiated 4CP notification
- OTH = Other

The survey responses from REPs in the competitive retail market indicated the numbers of customers enrolled in various types of programs. Aggregate numbers of customers (excluding customers enrolled in multiple programs) are provided in Table 1.2, while Table 1.3 identifies the types of energy consumers participating in each category of DR program.

Table 1.2: ESI IDs Participating in Only One Program (in Areas Opened to Retail Competition)

	4CP	BI	OLC	OTH	PR	RTP	TOU	Total
ESIID Count	10	22,947	10,071	733	1,877	4,105	117,570	157,313
REP Count	3	14	2	3	2	12	4	21

[3] Tables 1.1 through 1.3 were provided by ERCOT.

Table 1.3: Participation in Categories of Programs by Type of Energy Consumer[4]

ESIIDs Participating in Only One Program								
prof_type		program_type						
	total	4CP	BI	OLC	OTH	PR	RTP	TOU
BUSHILF	3,215		2,688		110		417	
BUSHIPV	1						1	
BUSIDRRQ	1,806	10	1,262		36	32	466	
BUSLOLF	1,983		1,075	1	108	17	768	14
BUSLOPV	15						2	13
BUSMEDLF	11,101		9,062	2	383	3	1,555	96
BUSMEDPV	6						1	5
BUSNODEM	8,320		7,456	2	76	5	604	177
BUSNODPV	3						1	2
BUSOGFLT	1,494		1,404				90	
NMLIGHT	1						1	
RESHIPV	148			4		2		142
RESHIWD	5			2				3
RESHIWR	58,455			4,224	9	768	50	53,404
RESLOPV	224			6		1		217
RESLOWD	1			1				
RESLOWR	70,535			5,829	11	1,049	149	63,497
total	157,313	10	22,947	10,071	733	1,877	4,105	117,570

Summary

A summary of the approach to quantifying impacts and the data sources used in the analysis of each type of demand response program is presented in Table 1.4.

The chapters that follow provide a detailed description of the analysis and findings for 4CP response and real-time pricing (combined with block and index pricing). Our analysis of the impacts from Other Load Control and Peak Rebate programs has been removed from this public version, in order to protect confidential information from disclosure.

[4] Please note "prof_type" stands for Profile Type.

Table 1.4: Summary of Programs, Data Sources, and Methods of Analysis

Program	Data Source	Method of Analysis
OLC - Other Load Control	• 15-minute interval consumption data (anonymized) from 05/01/2013 to 10/15/2013 for each ESI ID in this type of program. • Event information, as reported by two REPs operating larger programs (including start and stop times). • Start date for participation in the program, as reported by REP, for over 10,000 ESI IDs.	• Baseline analysis focused on events as reported by REPs. Impacts were calculated on a customer-specific basis, for each program. An historical baseline was constructed, same as the ERCOT ERS "Middle 8-of-10" methodology, and actual usage was compared against baseline usage to estimate demand response. (1)
4CP	• Aggregated IDR data for consumers served at transmission voltage for each regulated transmission and distribution utility (TDU) service area from 2001 to early 2014. • Evaluation was limited to use of aggregated (non-individual) data.	• A probabilistic analysis (logistic regression) was conducted to identify the days most likely to have elicited a 4CP response, based on weather, time of day, and other factors. • Baseline analysis focused on actual and potential 4CP days (summer weekday afternoons). Baselines excluded weekend days, holidays, prior CPs, and near-CPs. • Additionally, a regression model quantified the response of the aggregate usage of the transmission voltage customers in each TDU service area to 4CPs and "near 4CPs," while controlling for other factors.
RTP (Real Time Pricing) and BI (Block & Index)	• Anonymized data for 4,100 RTP customers and 23,000 BI customers (10/15/2011-10/15/2013), along with location-related information for each account. • Wholesale price data. • Start date for program, as reported by REP, for each ESI ID enrolled in this type of program. • Weather data.	• Regression baseline focused on pricing events, defined as LZ SPPs at three distinct price levels: o $300/MWh o $1,000/MWh o $3,000/MWh • Additional models were estimated looking at single price spike levels (e.g., just $3,000MWh). • An historical baseline was constructed, same as the ERCOT ERS "Middle 8-of-10" methodology, and actual usage was compared against baseline usage to estimate demand response.
PR (Peak Rebate)	• 15-minute interval consumption data (anonymized) for each ESI ID in this type of program.	• An historical baseline was constructed, same as the ERCOT ERS "Middle 8-of-10" methodology, and actual usage was compared against baseline usage to estimate demand response. (2)
TOU	*No analysis will be performed for TOU, at least for now. TOU price offerings are designed to promote a behavioral shift in customers and are not considered event-driven DR.*	
OTH	*No analysis is envisioned for OTH. ERCOT will bilaterally contact the REPs reporting "Other" products to better define the product types in future data collection exercises.*	
Notes:		
(1) A discussion of the data used to derive our estimate of the demand reduction from Other Load Control Programs has been removed from this "public" report, in order to protect confidential information from disclosure.		
(2) A discussion of the data and calculations used to derive our estimate of the demand reduction from Peak Load Rebate Programs has been removed from this "public" report, in order to protect confidential information from disclosure.		

Chapter 2: The Response of Large Industrial Energy Consumers to Four Coincident Peak (4CP) Transmission Charges

The Motivation to Avoid 4CP Intervals

In the areas of ERCOT opened to retail competition, large energy consumers with interval data recorders (IDRs) are charged for transmission services based on the individual consumer's contribution to four coincident peaks (4CPs), i.e., the 15-minute intervals of highest demand on the ERCOT system in each of four summer months -- June, July, August, and September. This chapter presents estimates of the degree to which large industrial energy consumers seek to reduce their demand, and thus their transmission costs, during periods in which 4CPs are set or there is a high likelihood that a CP will be set.

All energy consumers with a billing demand over 700 kW in a competitive area have an incentive to respond to the 4CP transmission prices. There is no apparent advantage to conducting this analysis on an individual-load basis, so aggregated or class-level data for energy consumers served at transmission voltage within each TDU service area were used. The data used were 15-minute interval aggregated load data for consumers with a non-coincident peak demand (billing demand) that exceeded 1 MW at least 10 times since January 2002 and were served at transmission voltage. Data for the summers of 2008 through 2013 were used in this analysis.

A consumer that can reduce its demand for electricity by 1 MW during each of the four CPs can save roughly $40,000 to over $55,000 in transmission charges the following year, as illustrated in Table 2.1 for energy consumers in the three largest transmission and distribution utility (TDU) services areas. This potential avoidance of transmission charges provides a strong incentive for industrial energy consumers with some flexibility in their operations to engage in "4CP chasing." These charges have been increasing in recent years and will continue to increase over the next couple years, as the costs associated with the Competitive Renewable Energy Zone (CREZ) projects are recovered.

Table 2.1: Example Savings Calculations for a 1 MW Reduction in Demand during 4CP Periods

	Monthly Charge per Previous Year's 4-CP kW	Annual Savings from a 1 MW demand reduction during 4CP periods
CenterPoint Energy (Docket Nos. 42053, 38339, and 41072; and base rates from tariff)		
Primary Voltage (with IDR; excluding Distribution Charge)	$3.4356	$41,226.97
Transmission Voltage (including Distribution Charge)	$4.0154	$48,184.27
Oncor (Docket No. 42059)		
Primary Voltage (with IDR)	$3.3259	$39,910.32
Transmission Voltage	$3.6055	$43,266.19
AEP-Texas Central (Docket No. 42054 and base rates from tariff)		
Primary Voltage (with IDR)	$4.6183	$55,420.02
Transmission Voltage	$3.7265	$44,718.00
Tariffs and TCRFs last accessed April 20, 2014. The calculations assume the customer has a power factor of one.		

The survey of LSEs conducted during the summer of 2013 identified very few customers who were involved in REP-initiated programs to provide 4CP warnings. However, many organizations other than REPs provide such services. Therefore the 2013 survey does not reflect the full numbers of industrial and institutional energy consumers involved in 4CP chasing.

Although industrial and institutional energy consumers served at primary voltage have about as much incentive to reduce their transmission costs by reducing demand during CPs as consumers served at transmission voltage, previous analysis could find no significant response among primary voltage consumers.[5] Consequently, the demand response of the smaller energy consumers served at primary voltage was not considered here.

Despite the significant potential savings, not all industrial and institutional energy consumers respond to transmission prices. For some facilities, a curtailment may impose economic costs upon some consumers in excess of the value of the potential savings in transmission costs. Energy consumers with the ability to easily interrupt or curtail their purchases from the grid and commit to providing an ancillary service to the ERCOT market (i.e., commit to curtail at the request of the system operator to provide an operating

[5] Zarnikau, Jay, Dan Thal (2013). "The response of large industrial energy consumers to four coincident peak (4CP) transmission charges in the Texas (ERCOT) market," *Utilities Policy*, Vol. 26, Sept. 2013, pp. 1-6.

reserve) cannot concurrently chase 4CPs. This could limit the response of an interruptible load that had elected to provide an ancillary service in ERCOT's day-ahead market or has an obligation with a load-serving entity through a bilateral arrangement to "be available" to provide a curtailment at ERCOT's request.

The following section identifies "near-CP" intervals and days. Near-CP days are excluded from baseline calculations and near-CP intervals are used as a variable in the regression analysis presented here. Chapter 3 provides estimates of the response of consumers served at transmission voltage to the 4CP-based transmission prices using an historical baseline approach. Chapter 2 uses a regression approach to explore the degree to which these two groups of large energy consumers respond to the transmission prices. The final section summarizes our findings and offers further observations.

Identification of Near-CP Intervals and Days

The timing of the CPs cannot be perfectly predicted. Until a summer month is over, the interval with the highest level of system demand is not known. It is particularly difficult to determine whether a hot day during the first week of a month will indeed set a CP, since weather forecasts for the later days of the month will not yet be widely available, and forecasts made early in a month will be uncertain. Further, a strong response to a likely CP may move the monthly peak demand to a different 15-minute interval within the same day or to another day.

Consequently, days when consumers are likely to have responded to a likely CP should be excluded from our calculation of savings from CP-chasing relative to an historical baseline, and in our regression analysis we are interested in detecting both 1) any reduction in demand during an actual CP and 2) during other intervals when a CP might have been considered probable. Thus, an identification of near-CPs is needed to implement both of the methods used to quantify the demand reduction during CPs.

To determine the intervals when consumers might have thought a CP was likely, a logistic regression model was used to estimate the historical relationship between a CP and a set of explanatory variables. Variables representing the month of the year and interval within the day were included to capture seasonal and diurnal factors affecting electricity use. The observations used in the estimation were confined to the nine 15-minute intervals from 3:00 pm through 5:15 pm (intervals 61 through 69) during weekday summer months in the years 2008 through 2013. In recent years, the monthly CPs during the summer have always fallen within this period. The variable *Interval61_62_63* is coded 1 for the period from 3 p.m. to 3:45 p.m. and 0 otherwise. Similarly, *Interval 64_65_66* was coded 1 for the period from 3:45 p.m. to 4:30 p.m. and 0 otherwise. Binary monthly variables were used to represent the months of June, July, and August. The real-time market price of electricity was included as an explanatory variable, to recognize that the response by consumers to a high price could change the odds of setting a CP, *ceteris paribus*. Alternatively, it might signal the possibility of a CP to a consumer monitoring market prices. The real time energy price is the market-clearing price of balancing energy during the period in which ERCOT had a zonal market structure, and the zonal average of locational marginal prices for the period since ERCOT adopted a nodal market structure. Energy prices (expressed in dollars per MWh) were obtained from ERCOT's website. Total system demand during the same interval of the previous day was included to recognize that patterns in demand across consecutive days may affect the likelihood of a CP, or the perception that one might occur. Finally, since summer peak loads are largely determined by air conditioning usage in Texas, a variable was constructed to represent the difference between the actual temperature in a central location within the ERCOT market (Austin) for a given interval and the highest temperature reading during the given month. Since interval-level temperature data were not available, it was assumed that all intervals within each hour had the same temperature.

Of course, at any given time prior to the end of the month, a consumer will not have complete information about hourly temperatures for the remainder of the month. Thus, our use of this variable implicitly assumes that a consumer has access to – and responds -- to reasonably accurate weather forecasts. As noted earlier, the uncertainty surrounding weather forecasts makes it more difficult to predict CPs that occur early in a month.

Estimation results are presented in Table 2.2. The greater the gap between the temperature of an interval and the highest temperature reading for the month, the lower the odds of setting a CP. An increase in energy prices and an increase in system load during the previous days tend to raise the odds of reaching a CP, holding other variables constant. While the dummy variable for intervals 61, 62, and 63 was significant, the dummy variables representing the month of the year and the variable representing the intervals 64, 65, and 66 did not have significant impacts. The high percent concordant suggests the predictive power of the model is satisfactory.

Table 2.2: Estimation Results from Logistic Regression Model used to Determine Probability of a CP

Variable or Statistic	Odds Ratio Estimate (p-value in parentheses)
Temperature Relative to Monthly Highest Temperature	0.490 (<.0001)
Energy Price in Real-Time Market	1.001 (.0003)
June Dummy	0.849 (.7728)
July Dummy	0.885 (.8310)
August Dummy	0.829 (.7427)
Interval61_62_63 Dummy	0.058 (.0062)
Interval64_65_66 Dummy	0.552 (.1493)
McFadden's Pseudo R^2	0.293

Scaling was performed to ensure that the probability of setting a CP over all intervals in a given month was equal to one. A new variable, *NearCP*, was created to represent intervals when the estimated probability was greater than 7%, yet a CP was not actually set. The 7% cutoff point was adopted since it resulted in roughly 50 15-minute intervals with a high likelihood of a CP (but no actual CP), as reported on Table 2.3. It was thought that it was reasonable for consumers to respond to roughly this number of possible CP events. Some of these near-CP intervals were on the same days as actual CP intervals.

Table 2.3: Identification of Near-CP Intervals

Year	Month	Day	Hour	Interval	Austin Temp. in F degrees
2007	6	19	16	68	94
2007	8	13	15	64	99
2007	8	13	17	69	98
2007	8	14	15	64	99
2007	9	27	16	67	94
2007	9	27	16	68	94
2008	8	7	16	67	100
2008	8	7	16	68	100
2008	9	2	15	64	100
2008	9	2	16	65	100
2008	9	2	16	66	100
2008	9	2	16	68	100
2009	6	25	16	67	104
2009	6	25	16	68	104
2009	6	25	17	69	104
2009	6	29	16	67	105
2009	6	29	16	68	105
2009	7	8	17	69	105
2009	9	3	16	65	99
2009	9	3	16	66	99
2009	9	3	16	67	99
2009	9	3	16	68	99
2009	9	3	17	69	98
2010	6	28	15	64	98
2010	6	28	16	67	97
2010	6	28	16	68	97
2010	8	23	16	65	104

Table 2.3: Identification of Near-CP Intervals – Continued

Year	Month	Day	Hour	Interval	Austin Temp. in F degrees
2010	9	1	15	64	98
2010	9	1	16	65	98
2010	9	1	16	66	98
2010	9	1	16	67	98
2010	9	1	16	68	98
2010	9	2	16	67	97
2010	9	2	16	68	97
2011	6	17	16	67	104
2011	6	17	16	68	104
2011	6	17	17	69	104
2011	9	12	16	67	104
2011	9	12	16	68	104
2012	6	26	15	64	106
2012	6	26	16	65	107
2012	6	26	16	67	107
2012	6	26	16	68	107
2012	9	4	16	67	103
2013	6	28	16	67	102
2013	6	28	16	68	102
2013	6	28	17	69	104
2013	7	30	17	69	102
2013	8	6	17	69	104
2013	8	8	17	69	104
2013	9	3	16	66	99
2013	9	3	16	68	99
2013	9	3	17	69	101

Estimating the Impacts with an Historical Baseline Approach

Our first attempt to quantify the impacts of the demand response associated with 4CP events involves comparing actual load to a baseline constructed using historical data. The baseline was constructed by averaging the load levels exhibited by this group of consumers during the previous "middle 8 of 10" weekdays. Thus, the same baseline approach discussed elsewhere in this report was applied here. Weekend days were not included in the baseline calculations, since no CPs were set on weekends during the timeframe studied here. Days with a near-CP interval, as identified in the previous section, were also omitted from the baseline calculation. If a CP from a previous month was within the historical period used to construct the baseline, then it was removed. Calculations were conducted separately for each

TDU service area. The historical baseline was then scaled, so that the total energy up to 15:00 (3 p.m.) for the baseline matched the total energy consumed up to 15:00 on the CP day.

Figures 2.1 to 2.8 compare the actual aggregate system-wide load of consumers served at transmission voltage to the baselines during each CP in 2012 and 2013. The response appears to be prominent and consistent. The period of response is typically 2 or 3 hours, since consumers do not know exactly which interval may set the CP.

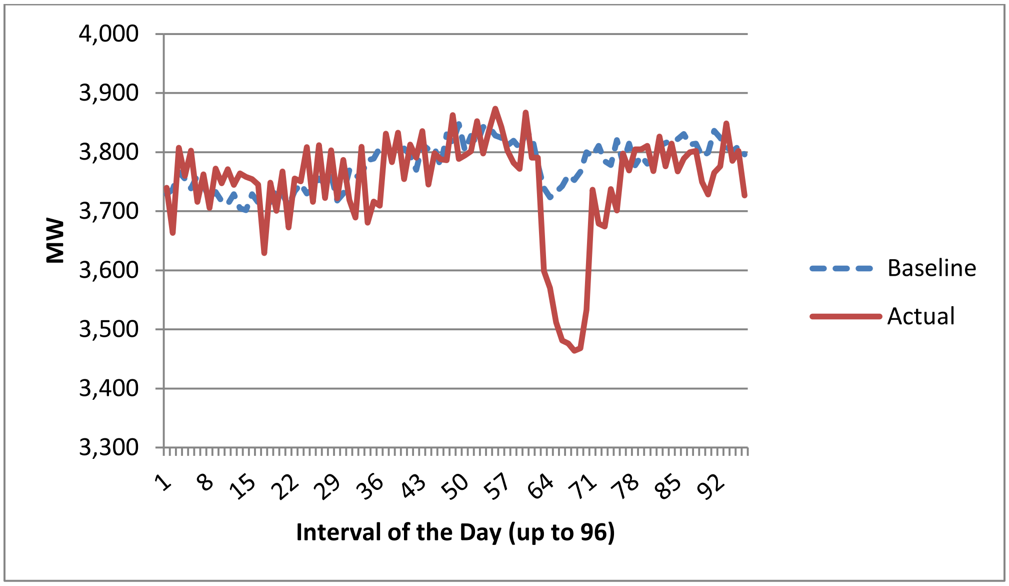


Figure 2.1: Energy Consumption (in kWh) by Transmission Voltage Customers on June 12, 2012, Contrasted against Baseline Energy

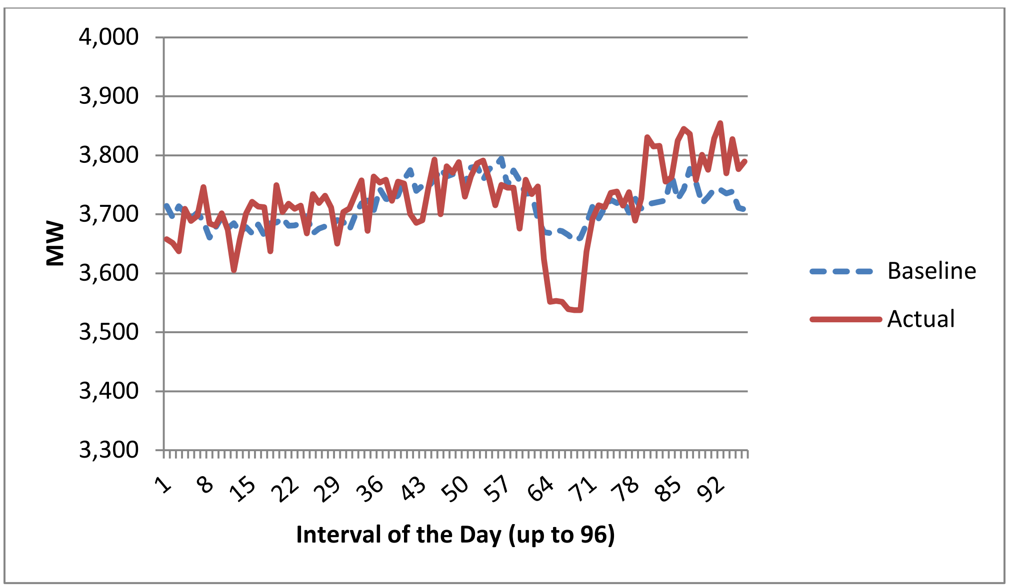


Figure 2.2: Energy Consumption (in kWh) by Transmission Voltage Customers on July 31, 2012, Contrasted against Baseline Energy

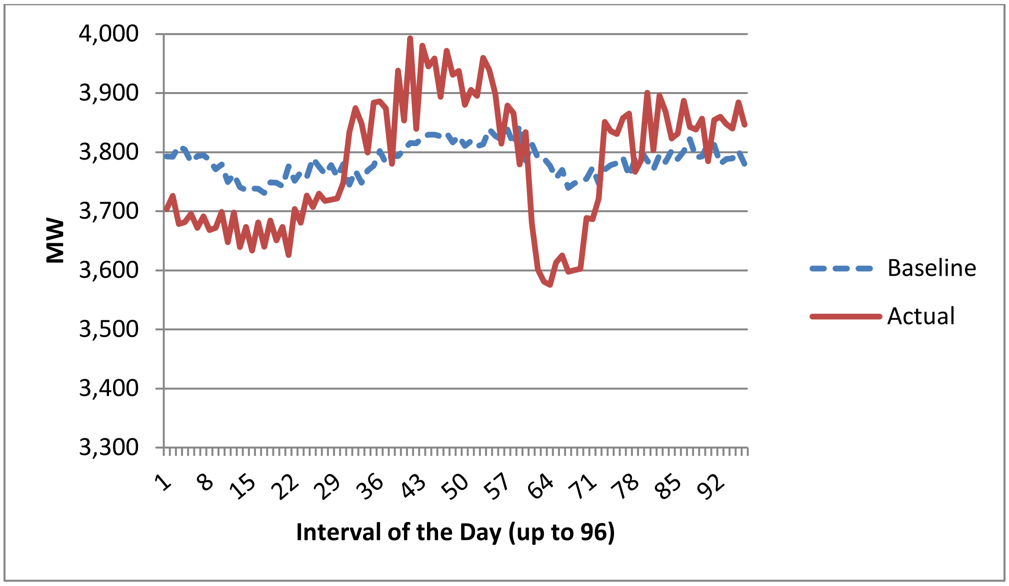


Figure 2.3: Energy Consumption (in kWh) by Transmission Voltage Customers on August 1, 2012, Contrasted against Baseline Energy

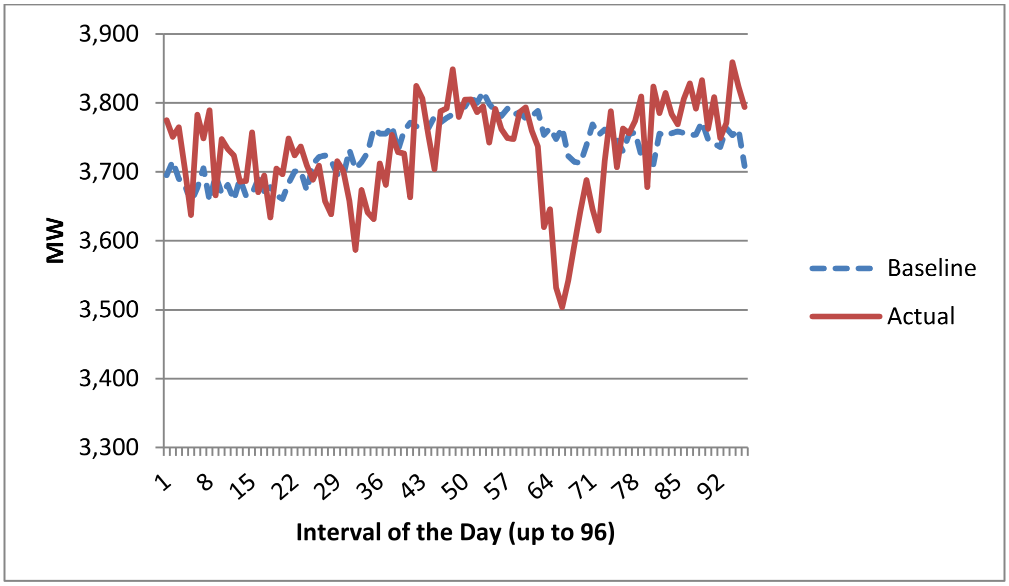


Figure 2.4: Energy Consumption (in kWh) by Transmission Voltage Customers on September 4, 2012, Contrasted against Baseline Energy

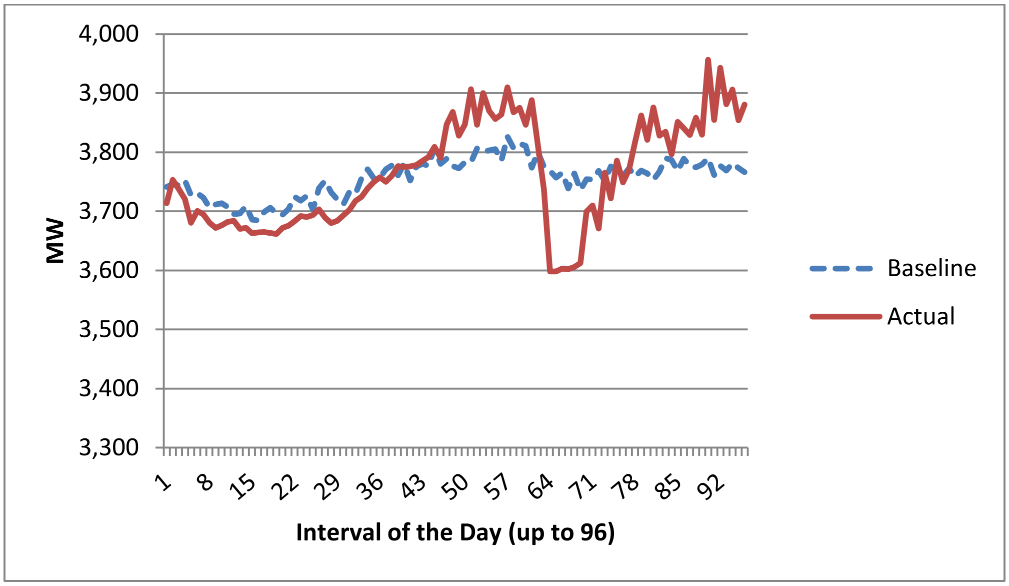


Figure 2.5: Energy Consumption (in kWh) by Transmission Voltage Customers on June 27, 2013, Contrasted against Baseline Energy

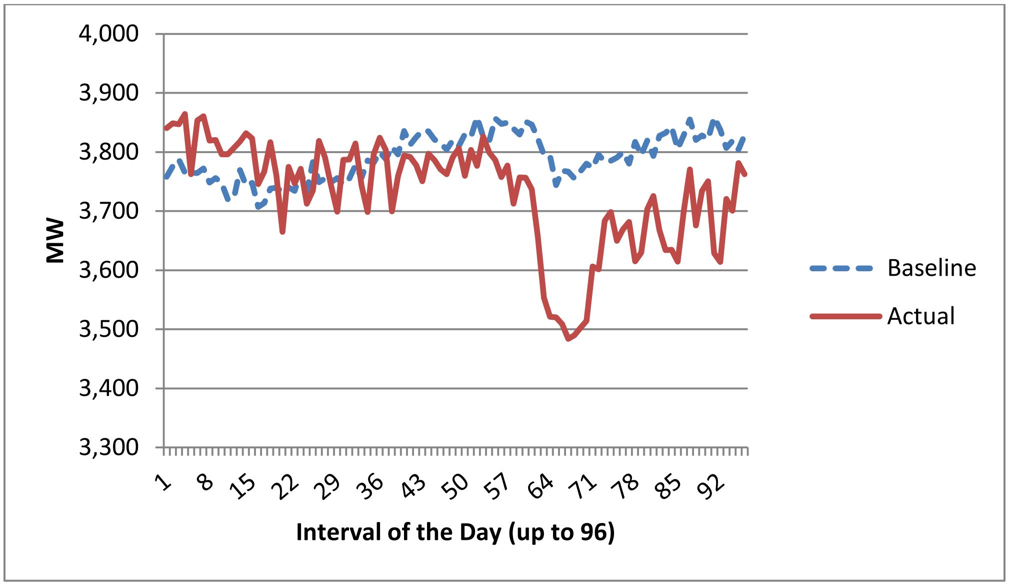


Figure 2.6: Energy Consumption (in kWh) by Transmission Voltage Customers on July 31, 2013, Contrasted against Baseline Energy

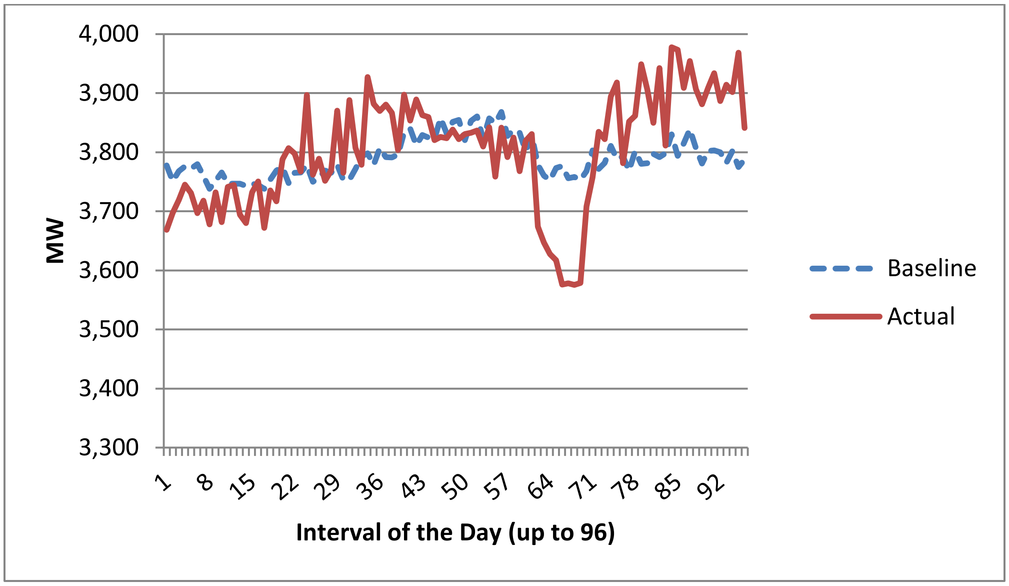


Figure 2.7: Energy Consumption (in kWh) by Transmission Voltage Customers on August 7, 2013, Contrasted against Baseline Energy

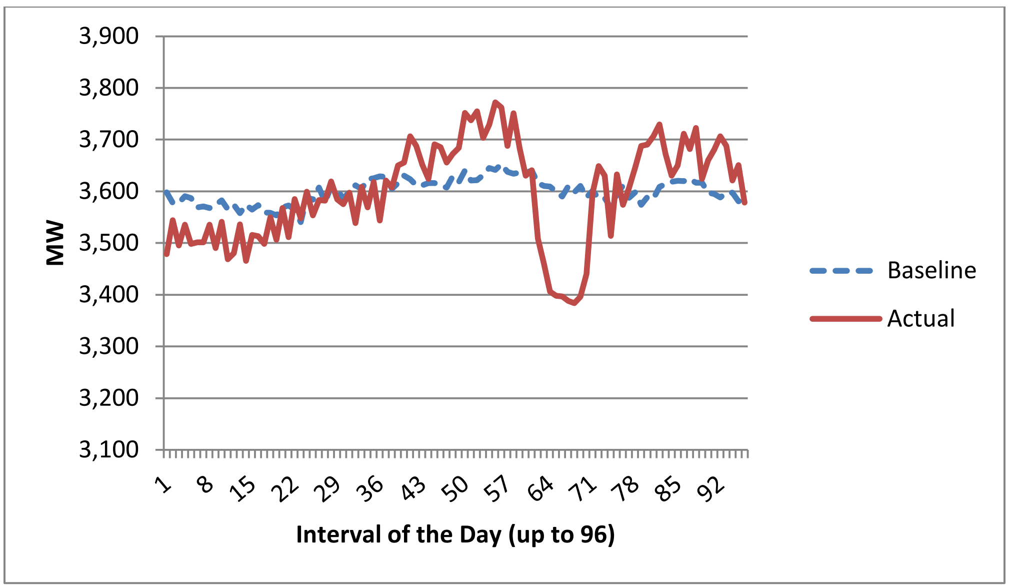


Figure 2.8: Energy Consumption (in kWh) by Transmission Voltage Customers on September 3, 2013, Contrasted against Baseline Energy

The estimated demand reduction during each of the CP events from 2007 through 2013 is provided in Table 2.4.

Table 2.4: Estimated Demand Reduction During CP Intervals

Year	Month	Day	Interval	Demand Reduction in MW
2007	6	19	16:45	-18
2007	7	12	16:30	28
2007	8	13	15:30	206
2007	9	7	16:00	263
2008	6	16	16:45	72
2008	7	31	16:45	220
2008	8	4	17:00	-116
2008	9	2	16:45	209
2009	6	25	16:15	111
2009	7	13	17:00	270
2009	8	5	16:00	167
2009	9	3	16:00	87
2010	6	21	16:45	87
2010	7	16	16:30	98
2010	8	23	16:00	294
2010	9	14	16:45	311
2011	6	15	17:00	264
2011	7	27	16:30	345
2011	8	3	17:00	230
2011	9	2	16:30	284
2012	6	26	16:30	238
2012	7	31	17:00	176
2012	8	1	17:00	178
2012	9	4	17:00	219
2013	6	27	17:00	304
2013	7	31	17:00	268
2013	8	7	16:45	268
2013	9	3	16:45	164

Response to transmission prices appear to be generally increasing over time. In recent years, consumers served at transmission voltage reduced their electricity purchases up to 4% during a summer CP, using an historical baseline calculation.

Where, within the ERCOT network, is the demand response to a 4CP event coming from? The two largest service areas account for over 80% of the demand reduction. The contributions from transmission voltage consumers in the Oncor and CenterPoint service areas were very similar. There was no noticeable demand response to 4CPs in the AEP-Texas North service area in 2013.

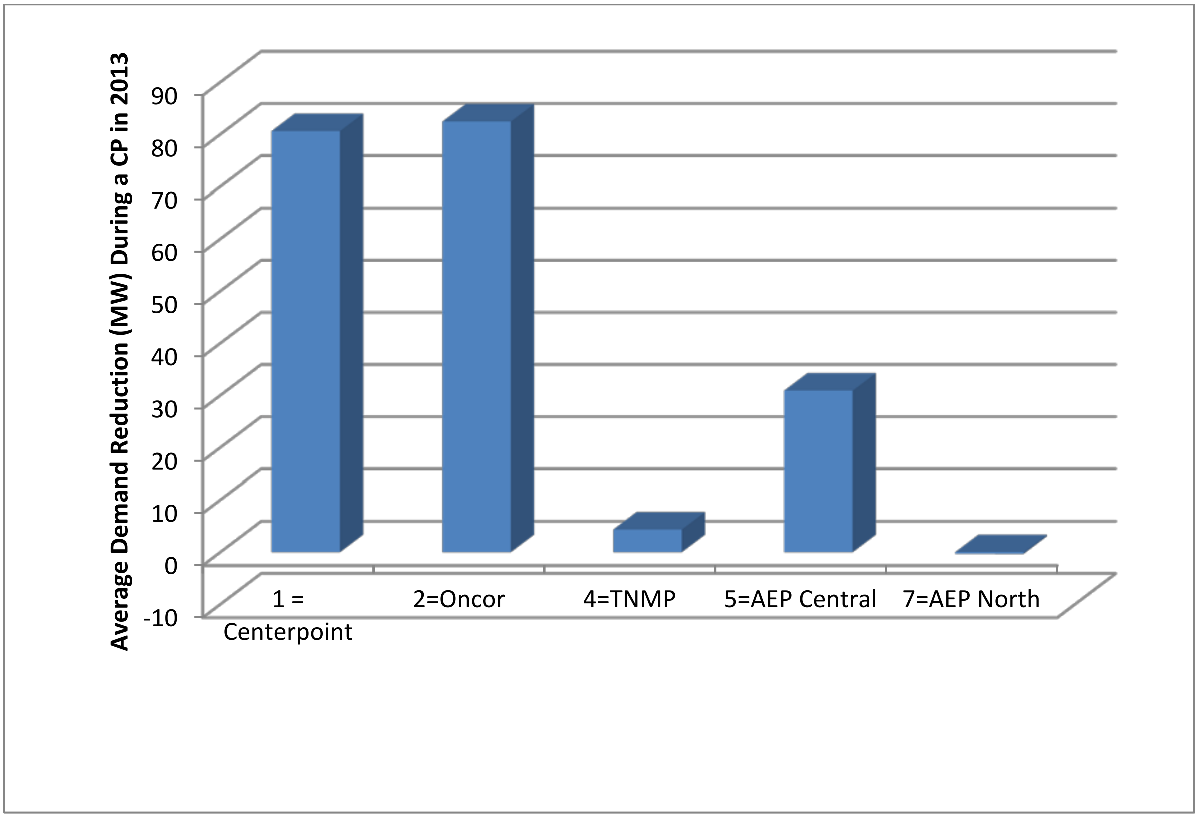


Figure 2.9: Distribution of the 4CP Response in 2013 by TDU Service Area

Regression Approach

A set of simple linear models was additionally used to detect whether the presence of an actual CP or *NearCP* had any detectable effect on the electricity consumption of energy consumers served at transmission voltage. This approach can better separate the effects of spikes in wholesale energy prices and local temperature from behavior designed to avoid the 4CPs.

Separate models were constructed for each TDU service area. The dependent variables represented the energy consumption of transmission voltage energy consumers, expressed in kWh per 15-minute interval. The explanatory variables were the real-time energy price (dollars per MWh), the presence of a CP (coded with a 1 if the interval was a CP and 0 otherwise), the *NearCP* variable discussed earlier (coded with a 1 if the interval had a high probability of setting CP and 0 otherwise), variables representing the month of the year and interval within the day to capture seasonal and diurnal factors affecting electricity use. Again, the variable *Interval61_62_63* represents the period from 3 p.m. to 3:45 p.m., while *Interval 64_65_66* covers the period from 3:45 p.m. to 4:30 p.m, five dummy variables representing year (year2008, year2009, year2011, year2012, year2013) to capture variation between years and one dummy variable "Ike" representing the widespread power outages due to hurricane Ike in 2008. The real time energy price (the same variable as was used in the logit model) was used to distinguish the response by consumers to a high market price of electricity generation from a 4CP-based transmission price. The temperature at a central location within each TDU service area was also used a as control variable. Data since the beginning of 2008 were used in the estimation, which treated the equations as a set in the estimation, applying Zellner's method for seemingly unrelated regressors (SUR).

Regression results are provided in Table 2.3. On average, over the period since 2008 and controlling for other factors, a CP reduces demand among energy consumers served at transmission voltage in the Oncor service area by 79MW (the coefficient of 19830.8 kWh/Interval * 4 Intervals/Hour /1000 to convert from kW to MW). Response in the Oncor service area to a near-CP is about 35% as great (27.6 MW = 6903*4/1000). Response to a CP in the CenterPoint area is about 52 MW. Estimation of the response by CenterPoint consumers to a near-CP yielded an implausible estimate (a positive coefficient), and the variable was consequently dropped from the model. It is also interesting to note that the consumers taking service at transmission voltage within the Oncor service area are particularly responsive to real-time energy prices.

Table 2.5: Estimated Impacts of CP Events and Other Factors on Load (in kWh) of Customers Served at Transmission and Primary Voltages by TDU Service Area

	CenterPoint Transmission Voltage Consumers (kWh/Interval)		Oncor Transmission Voltage Consumers (kWh/Interval)		TNMP Transmission Voltage Consumers (kWh/Interval)		AEP-Texas Central Transmission Voltage Consumers (kWh/Interval)		AEP-Texas North Transmission Voltage Consumers (kWh/Interval)	
Variable or Statistic	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
R^2	0.78		0.36		0.86		0.77		0.76	
Intercept	363677.3	<.0001	350369.8	<.0001	64856.54	<.0001	88657.47	<.0001	9992.432	<.0001
CP Interval	-15580.8	<.0001	-19830.8	<.0001	-1018.18	0.2368	-6706.68	<.0001	280.7897	0.0656
NearCP_High Probability Interval	NA	NA	-6903.33	0.0205	-770.56	0.1689	-25.6753	0.9723		
Energy Price in Real-Time Market in Local Zone	-2.35895	0.0001	-12.8803	<.0001	-0.088	0.6457	-0.92722	<.0001	-0.47994	<.0001
June Dummy	8043.149	<.0001	-20.5485	0.9819	-11.0228	0.9509	-609.731	0.0047	-50.9359	0.1052
July Dummy	7978.235	<.0001	468.9615	0.616	19.82816	0.9143	3502.168	<.0001	235.5142	<.0001
August Dummy	7001.718	<.0001	8596.896	<.0001	866.3201	<.0001	2591.734	<.0001	140.131	<.0001
Local Temperature (degrees F)	188.0845	<.0001	-211.927	<.0001	-63.6615	<.0001	205.8192	<.0001	41.51656	<.0001
Interval61_62_63 Dummy	2233.152	<.0001	4527.598	<.0001	407.4673	0.0056	615.9458	0.0008	-8.70573	0.7372
Interval64_65_66 Dummy	619.8589	0.2465	535.0589	0.4777	170.1504	0.2459	89.50766	0.6238	-10.0201	0.6993
year2008	28673.35	<.0001	10049.27	<.0001	-6497.35	<.0001	-9249.52	<.0001	-280.012	0.0002
year2009	10694.27	<.0001	-17219	<.0001	-8421.09	<.0001	-14360.8	<.0001	-1576.02	<.0001
year2011	6297.305	<.0001	13038.81	<.0001	8284.497	<.0001	7911.582	<.0001	-1260.18	<.0001
year2012	18258.21	<.0001	13883.01	<.0001	11891.87	<.0001	7969.366	<.0001	568.7932	<.0001
year2013	30939.03	<.0001	31638.89	<.0001	11704.42	<.0001	7134.617	<.0001	1350.582	<.0001
Ike	-183402	<.0001	NA	NA	-32601.1	<.0001	NA	NA	NA	NA

A system-wide estimation was also conducted, as presented in Table 2.6. In this estimation, the loads of transmission voltage energy consumers in all service areas were combined. Temperature data for Austin – a central location within the ERCOT market – were used to construct a weather variable. A simple average of the prices in the North and Houston zones were used to control for the effects of changes in energy prices. The coefficients were estimated using ordinary least-squares (OLS).

Table 2.6: ERCOT-Wide Estimated Impacts of CP Events and Other Factors on Load (in kWh) of Customers Served at Transmission Voltage

Variable or Statistic	Estimate	p-Value
R^2	0.75	
Intercept	992971.7	<.0001
CP Interval	-50259.8	<.0001
NearCP_High Probability Interval	-8884.02	0.0766
Energy Price, Average of North and Houston Zones	-19.3721	<.0001
June Dummy	5063.015	0.0007
July Dummy	12388.67	<.0001
August Dummy	19965.19	<.0001
Austin Temperature (degrees F)	-77.0511	0.3379
Interval61_62_63 Dummy	9056.429	<.0001
Interval64_65_66 Dummy	1770.888	0.1405
year2008	17410.7	<.0001
year2009	-40736.5	<.0001
year2011	45865.84	<.0001
year2012	61354.8	<.0001
year2013	90024.4	<.0001
Ike (for Hurricane Ike)	-257865	<.0001

These modeling results suggest that a CP has resulted in about 201 MW of demand response (four times the coefficient on the variable for CP Interval) on average over the past 5 years, after controlling for the effects of weather and energy prices. A near-CP event prompts a demand response of about 36 MW. Since the historical baseline analysis suggests that this response is increasing over time, higher values than these five-year averages should be expected in the future.

Conclusions

The historical baseline and regression methods provide very similar results. An average of the impacts for the 4CPs in 2013 estimated using an historical baseline approach as reported on Table 2.2 yields about 251 MW. Results from the regression analysis suggest that a CP has resulted in about 201 MW of demand response on average over the past 5 years. In addition to this response from large industrial and institutional energy consumers, NOIE utility systems and some REP programs may also contribute demand reduction during 4CPs.

Chapter 3: The Response of NOIEs to Four Coincident Peak (4CP) Transmission Charges

Non-Opt-In Entities (NOIEs) have an incentive to reduce their consumers' usage similarly to the incentive faced by large industrial and institutional energy consumers, as discussed in the previous chapter. NOIEs are charged for transmission services based on their contribution to ERCOT's system-wide four coincident peaks (4CPs), i.e., the 15-minute intervals of highest demand on the ERCOT system in each of four summer months -- June, July, August, and September. These already significant costs have been increasing in recent years and will continue to rise over the next couple years, as the Competitive Renewable Energy Zone (CREZ) project costs are recovered.

Unfortunately, our efforts to provide independent demand reduction estimates proved unsuccessful. Because ERCOT does not maintain NOIE customer data, only total usage data for the NOIE systems was available. We found it difficult to detect the impacts of relatively-small demand response programs using aggregate system-wide data for the NOIEs. The historical baseline approach described in the previous chapter was applied to the NOIE-system data for over 70 NOIEs. Baselines were developed for each NOIE and the NOIE-specific demand reduction during 4CPs was estimated. The results suggested no systematic pattern of 4CP response. For the sum of all NOIEs, demand was higher than the historical baseline for two of the CPs in 2013 and lower than the baseline for the other two. For most other years, there was a similar absence of any pattern. Figure 3.1 displays the demand reduction (or, lack thereof) achieved each year, calculated against the historical baseline described in the previous chapter.

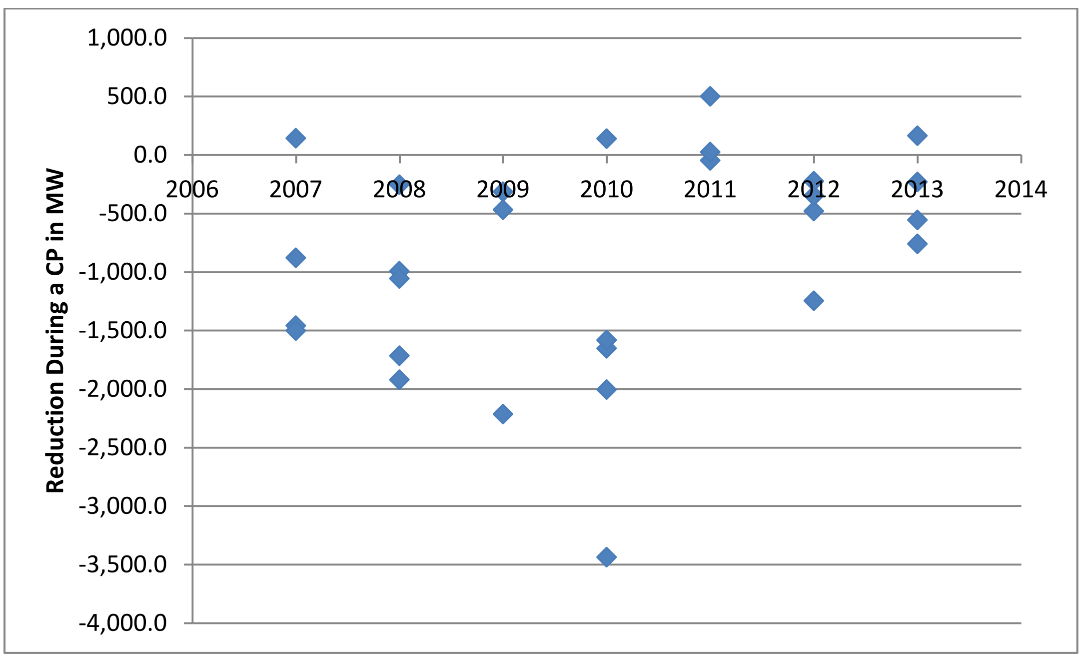


Figure 3.1: Aggregate Demand Reduction in MW of all NOIEs Relative to a 5-Day Adjusted Historical Baseline

A second attempt at an independent estimate of NOIE impacts from programs designed to reduce contributions to 4CPs focused on the two NOIEs that reported specific load control programs to ERCOT. Data for all other NOIEs were removed from the modeling. The results again were mixed, with both positive and negative estimates for peak demand reduction using both a 5-day historical baseline and a 10-baseline.

In summary, we have concluded that attempts to detect the impacts of NOIE-sponsored demand response programs using NOIE-system level data is too difficult and imprecise.

Our review of supplemental information provided by NOIEs with formal demand response programs suggests that they were very successful in predicting the timing of 4CPs in 2013 (although one of the NOIEs appears to have ended a direct load control deployment before the precise CP interval).

Chapter 4: RTP (Real Time Pricing) and BI (Block & Index)

General Description and Goal

A real-time pricing (RTP) rate provides customers with incentives to shift load from higher priced periods to lower priced periods. In the ERCOT market, wholesale electricity prices may change every 15 minutes of the day, and price spikes (extremely high price) may occur occasionally when the demand is high or generating capacity poses a constraint.

BI (Block & Index) pricing is a compromise between a fully indexed pricing and a fully fixed pricing. Under this purchasing strategy, buyers purchase part, or a "block," of their energy at a fixed price. The remainder of their energy is purchased at real-time prices (e.g., zonal averages of locational marginal prices).[6]

The goal of this analysis is to quantify any load reductions during price spikes during the period from October 2010 to October 2013. This analysis is somewhat limited, because there were rather few price spikes in ERCOT's wholesale market during this period.

Data Available

- Time Range:
  - October 15th, 2010 and October 15th, 2013. All customers who the REPs reported to have been served under a RTP or BI contract or program are included. Customers served by a NOIE under an analogous tariff or contract were not included.

- Customer demographic information:
  - To perform this analysis, the following information was obtained from ERCOT to each customer served under a RTP or BI contract or program:
    - Masked REP Code
    - Masked UIDESIID number
    - Profile Code: customer profile code
    - All of the data in a dataset of customers with Interval Data Recorders (IDRs) had a "BUSIDRRQ" code, all of the data in use have 1537 UIDESIIDs.
    - In a dataset of customers with 15-minute usage information collected with an Advanced Metering System (AMS), there were 11 profile types
    - Program start date
      This date is used to delete those who started RTP program later than the trade date. In other words, only those who have program start date earlier than trade date are used.

[6] http://energysmart.enernoc.com/bid/287786/Block-and-Index-Pricing-Model-Explained

Table 4.1: Profile Types

Profile Type	# of UIDESIIDs
BUSHILF	1944
BUSHIPV	1
BUSLOLF	1688
BUSLOPV	2
BUSMEDLF	5274
BUSMEDPV	1
BUSNODEM	2824
BUSNODPV	1
BUSOGFLT	1356
RESHIWR	48
RESLOWR	116

- Weather and Price Data:
  - In our modeling, we sought to control for the effects of temperature when estimating the response of these energy consumers to price spikes.
  - To enable us to test our modeling at a few different levels of geographic granularity, we collected weather data for four settlement zones: north region, south region, Houston region and west region.

We used Austin hourly weather data for an ERCOT-wide model run, given Austin's central location in the ERCOT power region.

- Price Data:
  - For our ERCOT-wide model run, we used the North zone's real time market 15-minute interval price (LMPz) to develop variables to represent price spikes. ERCOT north settlement zone is the largest region within the ERCOT market.

- Consumption Data:
  - 15-minute interval kWh consumption data for each customer with traditional IDR meter, one day for each row. All the customers in this dataset in use have a profile code of BUSIDRRQ.
  - 15-minute interval kWh consumption data for each customer with advanced meter, one day for each row. There are 11 profile types are in this dataset.

Methodologies

Regression method was used to estimate load reduction of RTP customers with AMS customers. Two methods were used to estimate load reduction of RTP customers with IDR meters: regression analysis and ERCOT's ERS "8-of-10" baseline methodology.

1. Regression Analysis

Regression analysis is used to detect the potential relation between load reduction and price spike. One advantage for regression analysis is that it can control the weather factor and focus solely on the load reduction caused by price spike to some extent. For both IDR and AMS dataset, we applied the following regression model equation for each profile type.

We first estimated a regression model on an ERCOT-wide basis, using:

Consumption = $\beta_0 + \beta_1$ * austincdh + β_2 * austinhdh + β_3 * mon + β_4 * tue + β_5 * wed + β_6 * thu + β_7 * fri + β_8 * sat + β_9 * northspike300 + β_{10} * northspike1000 + β_{11} * northspike3000 + β_{12}* year2011+ β_{13}* year2012+ β_{14}* year2013;

In the equation above:

- Consumption: average 15-minute kWh consumption for each profile code
- austincdh: Austin cooling degree hours. Balance point is set as 65F. austincdh = max(Austin temperature at that hour – 65,0).
- austinhdh: Austin heating degree hours. Balance point is set as 65F. austinhdh = max(65 - Austin temperature at that hour,0).
- mon-sat: A set of dummy variables to control for day-of-week factor. For example, mon = 1 if that day is Monday, otherwise mon = 0. Other variables are designed in the similar manner.
- northspike300: dummy variable indicating price spike. If price in north region > 300, then northspike300 = 1, otherwise northspike300 = 0.
- northspike1000: dummy variable indicating high price spike. If price in north region > 1000, then northspike1000 = 1, otherwise northspike1000 = 0.
- northspike3000: dummy variable indicating extreme price spike. If price in north region > 3000, then northspike3000 = 1, otherwise northspike3000 = 0.
- year2011, year2012, and year2013: dummy variables indicating year, with year 2010 as baseline year.

Due to considerable heterogeneity in this group and varying dates at which customers enrolled in these programs (more than 80% of the customers joined the RTP/BI program during the three-year period), these three dummy variables can explain a great deal of variation of average consumption change over the year.

2. ERCOT ERS "8-of10" Baseline Methodology

The coefficients of northspike, northspike1000 and northspike300 will show a rough picture of how customers reduce their energy usage gradually as prices increase.

Since there is only one profile type in the IDR dataset, the model is run only once. There are 11 profile codes in the AMS (advanced meters) dataset, the model is run 11 times for that dataset consequently.

A disadvantage of this ERCOT-wide estimation is that Austin weather data may not match the weather actually experienced by the consumer, given the state's large size and climatological diversity. And the North zone's wholesale prices may not exactly match the prices faced by RTP and BI customers in the Houston, South, and West settlement zones.

This led us to also estimate models for various settlement zones within ERCOT. OncorTNMP Region (Dallas-Fort Worth area), CenterPoint Region (Houston area), AEPCentral Region (South area) and AEPNorth (West area). We used corresponding weather data and real-time 15-minute price data, running similar models mentioned above. We use customers' zip code to match their service area.

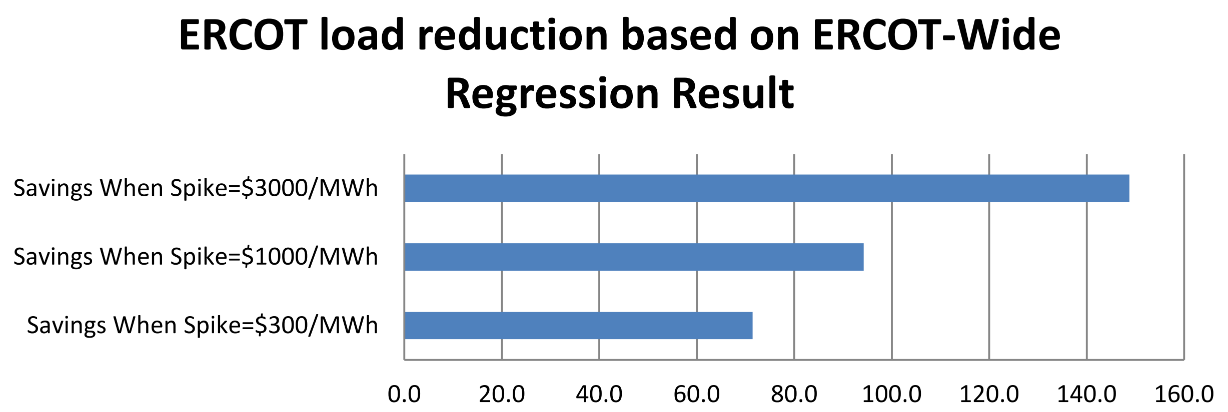
Results and Interpretation

The ERCOT-wide regression results for traditional meter is as follows:

Table 4.2: Table Results for IDR (Traditional Meter) Dataset

Parameter	Estimate	Approx P-Value
Intercept	263.6523	<.0001
cdh	2.147348	<.0001
hdh	-0.97035	<.0001
mon	16.95715	<.0001
tue	22.68545	<.0001
wed	23.4731	<.0001
thu	25.31967	<.0001
fri	24.65566	<.0001
sat	7.279482	<.0001
spike300	-11.6215	<.0001
spike1000	-3.70562	0.3119
spike3000	-8.86777	0.0934
year2011	32.67268	<.0001
year2012	47.59334	<.0001
year2013	121.9359	<.0001

As we can see from the result, the coefficients of spike300, spike1000 and spike3000 show us the 15-minute kWh usage reduction in a price spike. Based on the coefficients above, we can estimate the MW load reduction for different price spikes:



	Savings When Spike=$300/MWh	Savings When Spike=$1000/MWh	Savings When Spike=$3000/MWh
ERCOT	71.4 MW	94.2 MW	148.8 MW

Figure 4.1: ERCOT Load Reduction Based on ERCOT-Wide Regression Results

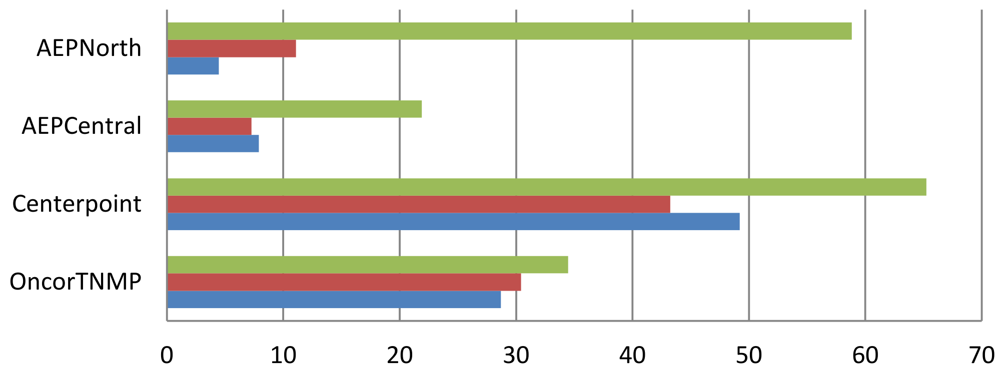
As we can see from the Figure 4.1, we can get an overall load reduction of 71.4MW if the price spike is set at $300/MWh. We can get an overall load reduction of 94.2MW if the price spike is set at $1000/MWh. We can get an overall load reduction of 148.8MW if the price spike is set at $3000/MWh.

The region-based regression results for IDR meters are presented in Table 4.3.:

Table 4.3: Region-Based Regression Results for IDR Meters

Parameter	OncorTNMP Estimate	Adjusted P-value	CenterPoint Estimate	Adjusted P-value	AEPCentral Estimate	Adjusted P-value	AEPNorth Estimate	Adjusted P-value
R^2	0.3859		0.7061		0.6329		0.7368	
intercept	272.8794	<.0001	331.0149	<.0001	161.8939	<.0001	159.1689	<.0001
cdh	2.02035	<.0001	3.5562	<.0001	3.816527	<.0001	1.090409	<.0001
hdh	-0.11518	<.0001	-1.22374	<.0001	0.008857	0.8406	-1.10035	<.0001
mon	21.43919	<.0001	23.46694	<.0001	15.50464	<.0001	1.098698	0.0618
tue	33.41428	<.0001	26.77246	<.0001	21.44107	<.0001	0.039425	0.9467
wed	37.67381	<.0001	24.89043	<.0001	22.52676	<.0001	2.179524	0.0002
thu	41.25911	<.0001	25.56702	<.0001	20.00804	<.0001	2.370597	<.0001
fri	38.07965	<.0001	25.96479	<.0001	21.31024	<.0001	3.725477	<.0001
sat	11.65019	<.0001	6.557132	<.0001	12.14564	<.0001	0.883711	0.1335
spike300	-13.5334	<.0001	-19.8066	<.0001	-14.1144	0.0003	-4.51961	0.0161
spike1000	-0.81206	0.8698	2.401403	0.5578	1.162505	0.871	-6.74183	0.1953
spike3000	-1.90622	0.7887	-8.86314	0.1485	-26.1713	0.0181	-48.525	<.0001
year2011	-2.06366	0.0002	-26.1882	<.0001	-69.5993	<.0001	194.3828	<.0001
year2012	14.58787	<.0001	1.017165	0.0364	-64.0176	<.0001	209.8581	<.0001
year2013	46.1671	<.0001	80.18717	<.0001	119.2617	<.0001	320.6365	<.0001

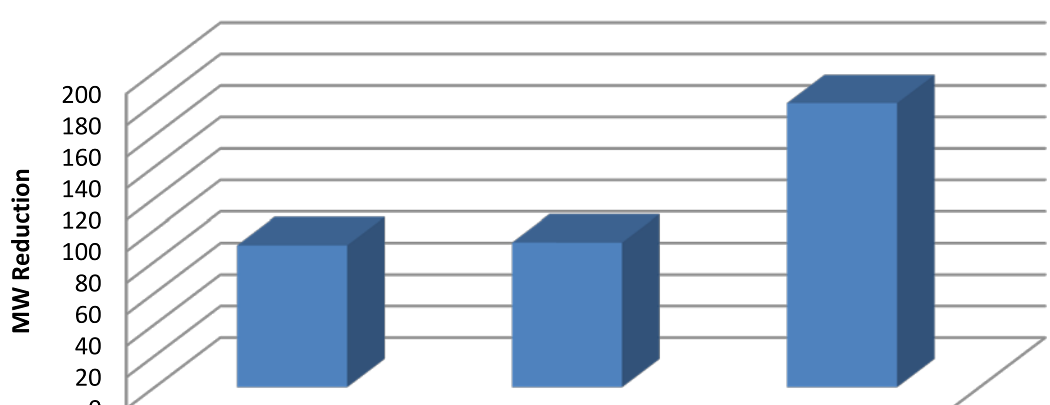
As we can see from the result, the coefficients of spike300, spike1000 and spike3000 show us the 15-minute kWh usage reduction in a price spike. Based on the coefficients in Table 4.3, we can estimate the MW load reduction for different price spikes in four areas:



	OncorTNMP	Centerpoint	AEPCentral	AEPNorth
MWSaving when spike = 3000	34.4535616	65.25055656	21.9089892	58.82985696
MWSaving when spike = 1000	30.4123752	43.2345168	7.2530612	11.08125696
MWSaving when spike = 300	28.690808	49.1995944	7.904064	4.44729624

Figure 4.2: Load Reduction (MW) By Region

The Overall load reduction calculated by summarizing four areas is graphed as shown in Figure 4.3:



	Savings When Spike=$300/MWh	Savings When Spike=$1000/MWh	Savings When Spike=$3000/MWh
ERCOT	90.2 MW	92.0 MW	180.4 MW

Figure 4.3: ERCOT Load Reduction Based on 4 Areas: Regression Results

Using this approach, we can get an overall load reduction of 90.24MW if the price spike is set at \$300/MWh. We can get an overall load reduction of 91.98MW if the price spike is set at \$1000/MWh. We can get an overall load reduction of 180.44MW if the price spike is set at \$3000/MWh.

An alternative ERCOT ERS "8-of-10" baseline methodology was also adopted.

Since this method is event-based, we set intervals with north region price higher than \$3,000/MWh as events. During Oct.15th, 2010 – Oct.15th, 2013, there were 70 events (intervals) in total. After using ERCOT's ERS "8-of-10" baseline methodology, the results are on Table 4.4 below:

Table 4.4: ERCOT ERS "8-of-10" Baseline Methodolgy Procedure and Results

Year	Month	Day	IntervalDuration	MW Savings	#Of Customers In Use
2011	3	3	76	-3.00	292
2011	6	27	63	0.86	374
2011	8	1	60	-10.29	380
2011	8	2	63-68	-0.46	380
2011	8	3	61-70	10.30	380
2011	8	4	55-65	30.20	380
2011	8	5	61-68	7.48	380
2011	8	23	64,65,67,68	-2.76	382
2011	8	24	57-67	28.72	383
2013	4	5	28	181.88	1192
2013	9	3	67	90.09	1531
Note that Feb 2nd, 2011 price spike event was deleted due to overlapping ERCOT EEA and ERS deployment.					

As we can see from the results in Table 4.4, load savings vary by a great deal, ranging from -10MW to 182MW. Thus, some of the events with high levels of estimated demand reduction as estimated with this historical baseline approach are consistent with the 148.75 MW of demand reduction estimated with a regression approach on ERCOT-wide basis. And we can also see that more than 1,200 customers joined the program gradually during the less-than-3-year period, also partly explained the variations in this part of result.

Further Analysis - Breakdown Analysis by Customer Size

Due to significant heterogeneity in customer size and variation in program joining dates (and correlation between these, as several large customers joined late in the analysis period), Frontier performed an additional analysis in which we split RTP program participants into two groups by size. A simple overall 15-minute average consumption was used as the criterion to group customers by size. Customers consuming more than 5000kWh in 15-minute intervals went into the large customers group, while the rest were placed in a "small" customer group.

Large Customers

In the RTP traditional meter (IDR) dataset group, only 31 of the 1537 customers belong to the large customer group. Among these 31 customers, 27 of them joined the respective RTP/BI rate offerings after April 2012. If price spike event threshold is set as $3,000/kWh, as we can see from Table 4.4, only 2 events occurred after April 2012. Regression is not appropriate in this case due to too few price spikes. Therefore, Frontier used the 'middle 8-of-10 days' baseline method to calculate load reduction for the large customer group for price spike events on April, 5th and September, 3rd 2013.

Calculation Procedures and Results

Using the same "8-of-10" baseline methodology applied to ERCOT's ERS program, the load reduction estimates for these two events contributed by this group are presented in Table 4.5.

Table 4.5 ERCOT ERS "8-of-10" Baseline Methodology Procedure and Results for Bigger-Size Group

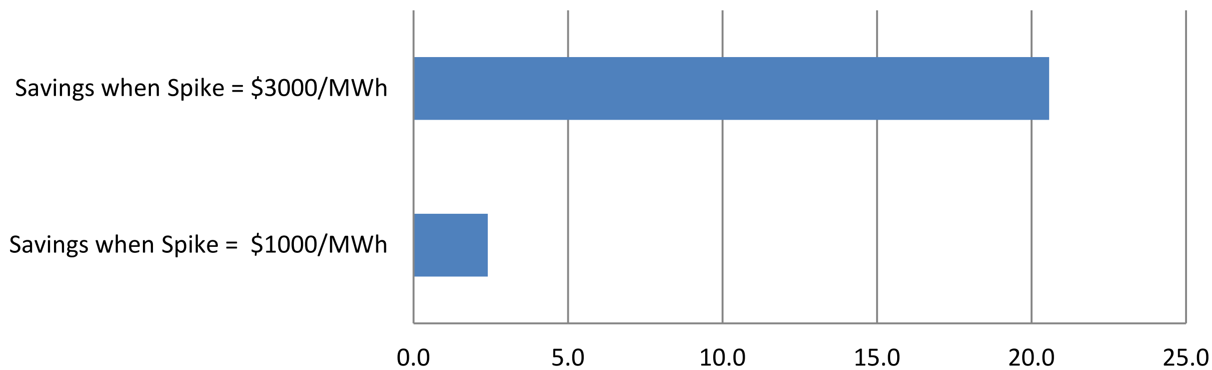
Date	Interval	MW Savings	# Of Customers In Use
4/5/2013	28	133.67	24
9/3/2013	67	87.06	31

As we can see from Table 4.5, these 31 customers alone contributed load reductions of 134 MW and 87 MW respectively during these 2 events, while the overall customers (1537 customers): these load reductions represented 74 and 97 percent, respectively, of total load shed for these 2 events (totals of 182 MW and 90 MW load reductions, as shown in Table 4.4. For these two events, the large customers contributed most of the load reduction.

Smaller Customers

Frontier applied regression analysis for the smaller customers group to estimate their load reduction. Since smaller customers tend to be less sensitive to price signals, some of them may not respond until the price is higher. Based on this assumption, we removed the spike300 variable from this analysis, leaving only the two price spikes dummy variables: spike1000 and spike3000. The regression-based load reduction estimates for the smaller- customers group by region are as follows:

Figure 4.6: Smaller-Size Customer Group Load Reduction Based on 4 Areas Regression Results



	Savings when Spike = $1000/MWh	Savings when Spike = $3000/MWh
ERCOT	2.4 MW	20.6 MW

As shown in Figure 4.4, although the RTP rate participants in the smaller customers group provide about 21 MW of load reduction when prices spike to $3000/MWh. Although they account for more than 95% of the customers in RTP rate programs, they only contribute between 15 and 25 percent of total load reduction (as compared to the 87 and 134 MW provided by the large customers to the two events evaluated in Table 4.5.

Results

This analysis shows that the smaller customers make small contributions, individually, to overall load reduction by RTP rate program participants during price spikes. Most of the load reduction is driven by large customers. Overall, the results of this analysis are consistent with the observations from the original analysis: it shows load shed on the order of 155 MW in the largest event (134 MW from large customers plus 21 MW from smaller customers according to the regression analysis), a result similar to the 148 MW reported in Figure 4.1. These two results are also generally consistent with the 8-of-10 baseline methodology results for overall ERCOT-wide data provided in Table 4.4. Since most of the larger customers joined the RTP/BI program during the past 2 years and only experienced 2 or less price spikes, Frontier believes it is reasonable to conclude that the findings for the most recent events are the most representative of the load reduction capacity in RTP rate programs for the future.

Results for AMS (Advanced Meter) Dataset

Unlike traditional meter users, advanced meter users consume relatively small amount of energy. Although there are some significant load reductions for most profile type groups, the overall load reduction for this dataset is trivial compared with IDR group. The preliminary results are summarized in Table 4.7.

Table 4.7: Results for AMS (Advanced Meter) Dataset

Profile Type	Spike300 Coefficient	# of Individuals	MWSavings
BUSHILF	-0.9434	1944	7.335878
BUSHIPV	-1.8511	1	0.007404
BUSLOLF	0.5505	1688	-3.71698
BUSLOPV	-0.2773	2	0.002218
BUSMEDLF	0.2811	5274	-5.93009
BUSMEDPV	-0.0415	1	0.000166
BUSNODEM	-0.061	2824	0.689056
BUSNODPV	-0.1589	1	0.000636
BUSOGFLT	-0.6726	1356	3.648182
RESHIWR	-0.341	48	0.065472
RESLOWR	0.1507	116	-0.06992
Summary	**NA**	**13255**	**2.032027**

As we can see from the table above, the overall load reduction for this group is around 2MW. The result is relatively small compared with the IDR group.