LBNL-54761

ERNEST ORLANDO LAWRENCE
BERKELEY NATIONAL LABORATORY

Customer Response to Day-ahead Wholesale Market Electricity Prices: Case Study of RTP Program Experience in New York

Appendix

C. Goldman, N. Hopper, O. Sezgen, M. Moezzi and R. Bharvirkar
Energy Analysis Department
Ernest Orlando Lawrence Berkeley National Laboratory
University of California Berkeley
Berkeley, California 94720

B. Neenan, R. Boisvert, P. Cappers, D. Pratt
Neenan Associates

Environmental Energy
Technologies Division

June 2004

http://eetd.lbl.gov/ea/EMS/EMS_pubs.html

The work described in this report was coordinated by the Consortium for Electric Reliability Technology Solutions and funded by the California Energy Commission, Public Interest Energy Research Program, under Work for Others Contract No. 150-99-003, Am #1 and by the U.S. Department of Energy under Contract No. DE-AC03-76SF00098.

Disclaimer

This document was prepared as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor The Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or The Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, or The Regents of the University of California.

Ernest Orlando Lawrence Berkeley National Laboratory is an equal opportunity employer.

Appendix A: Regulator and Stakeholder Interview Protocol

Lawrence Berkeley National Laboratory and Neenan Associates (LBNL's sub-contractor) have received funding from the California Energy Commission (CEC) to conduct a case study of Niagara Mohawk's real time pricing program that assesses customer response to tariffs based on day-ahead wholesale market prices (i.e., RTP) in a retail competition environment.

The CEC (and CPUC) are interested in the regulatory and policy experience in New York, as these agencies are currently examining issues in developing dynamic pricing tariffs for California and are analyzing the merits of alternative strategies (e.g., "real-time pricing" tariffs, price-responsive load bidding programs administered by ISOs) that seek to increase customer participation in electricity markets.

As part of this research, we are conducting interviews about the regulatory proceeding that led to the adoption of Niagara Mohawk's SC-3A Option 1 electricity tariff in 1998 and customer experiences with "real-time" pricing tariffs during the last four years. As a key actor in this proceeding, your insights into the process, major policy and program design issues, lessons learned and suggestions for other policymakers and regulators are of great interest to policymakers in California.

<u>Introduction/ Overview</u>

1. Please provide the following information about yourself:

    a. Name:
    b. Organization:
    c. Title:
    d. Address:
    e. Phone:
    f. Fax:
    g. E-mail:

2. Please describe your role in the regulatory proceedings (Cases 94-E-0098 and 96-E-0134) that led to the adoption of the NMPC SC-3A Option 1 tariff in 1998.

3. In your opinion, what were the most important regulatory/policy issues pertaining to this tariff?

<u>Process/ Goals</u>

4. What were the NYPSC's overarching policy goals? How did NMPC's proposed Option 1 tariff support those goals?

5.a. Describe the regulatory process and the approach used to implement the tariff (e.g., contested rate case, settlement, rulemaking/workshop).

b. How long did the process take?

6. How receptive was NMPC to the idea of RTP? What were the major issues over which it was concerned? If so, how were they resolved?

7. Were similar proceedings attempted in other utility service territories in New York? If so, what factors account for their lack of implementation?

<u>Competing Proposals & Tariff Design Issues</u>

8. NMPC already had a pilot RTP program in place that employed a 2-part tariff with customer baseline loads (CBL). Why was a different, 1-part (market-based) tariff design proposed instead?

9. What was the rationale for the decision to bill T&D charges as a demand charge (per kW), rather than a volumetric (per kWh) charge?

10. Aside from the tariff that was actually implemented, were there competing proposals? If yes, please describe them. Who was responsible for offering them?

Ultimately, RTP was offered as the default electricity service to large commercial/ industrial customers under Option 1. In addition, an alternative fixed-price time-of-use tariff was offered under a five-year contractual agreement as Option 2.

11. Was there strong debate over the legality or appropriateness of providing a RTP tariff as the default service? If so, how was this issue resolved?

12. How and why was the decision to offer Option 2 made? How/why was the 5 year contract length arrived at? What options will customers on this tariff have when the contracts expire next year?

13. How were the alternative fixed-price tariff electricity supply service rates (per kWh) arrived at? Was there controversy over the appropriate risk premium to include? If yes, how was this issue resolved?

14. What criteria were used by the NYPSC in their decision to adopt this tariff structure? Did customer ease of understanding constitute a major criteria for evaluating potential tariff designs?

15. How much weight did the following equity concerns have in the decision to adopt the RTP tariff vs. other options?

    a. *ability of program to provide net system benefits (e.g., net cost reductions)*
    b. *revenue neutrality by customer class*
    c. *revenue neutrality by customer*
    d. *non-discrimination by size or end-use*
    e. *minimization of gaming opportunities*

16. Please rate the importance of the following issues in the regulatory proceeding (1= LEAST IMPORTANT, 5=MOST IMPORTANT).

Potential Issue	Importance
voluntary vs. mandatory tariff	
utility risk exposure	
revenue neutrality (utility perspective)	
one-part vs. two-part tariff	
establishing customer baseline load (CBL)	
transmission & distribution (T&D) utility cost recovery	
customer acceptance	
customer equity concerns	
customer risk exposure	
offering ways to limit customer risk	
overall system benefits (e.g., lowered costs, grid reliability)	
level/reliability of demand response potential	
program costs	

Tariff Implementation Costs

17. How significant a factor was cost in deciding on the RTP tariff vs. other options?

18. Were there significant incremental costs involved in adopting the RTP tariff (e.g., infrastructure costs, O&M and financing carrying costs, marketing and education costs, customer costs, scalability of infrastructure)?

19. Were there cost-effectiveness issues? Was a cost/benefit analysis performed?

Relative Importance of SC-3A Option 1 Tariff and Demand Response Programs

20. In your opinion, what is the relationship between RTP and other demand response programs? What are the strengths and weaknesses of the different approaches?

21. Please compare the relative effectiveness of the Option 1 tariff to the Day Ahead Demand Response Program (DADRP) in delivering the benefits described below (1=RELATIVELY INEFFECTIVE, 5=EXTREMELY EFFECTIVE):

Demand Response Benefit	**Option 1 tariff**	**DADRP**
size of demand response (MW)		
focus of response when and where needed		
year-round availability		
encouragement of peak-load reduction		
encouragement of load shifting		
encouragement of off-peak load building		
potential for system benefits from response (e.g., decreased grid congestion, lowered costs)		
sustained potential for participation		

RTP Tariff Results

22. What was the expected level of demand response (MW) from the RTP tariff? In your opinion, has this materialized?

23. What level of participation (number of customers) was expected from the RTP tariff vs. the alternative fixed-rate tariff offered? Did the high (~80%) subscription rate come as a surprise?

Summary

24. In your opinion, has the NMPC large customer RTP tariff been successful at accomplishing the goals it was meant to address? Why or why not?

25. What, in your opinion, were the most significant barrier(s) to overcome in the regulatory process? What factor(s) were most conducive to its success?

26. If the process could be repeated from scratch, what would you recommend be done differently? What would you leave unchanged?

Appendix B: Customer Survey

1. Please verify the following contact information we have for you so that upon completing this survey, we may properly enter you into the prize drawing.

1.Name: ____

2.Organization: ____

3.Address: ____

____

4.Phone: ______________________ *5.Fax:* ______________________

6.E-mail: ______________________

We are going to ask you a series of questions concerning your business and the ways in which you respond and adapt to changes in electricity prices. Please answer specifically for the location you have just given us, even if you have other facilities or locations in the state or around the country

2. What is your position/title in the organization?

- ❑ 1. FACILITY MANAGER
- ❑ 2. ENERGY MANAGER
- ❑ 3. PURCHASING/PROCUREMENT MANAGER
- ❑ 4. GENERAL MANAGER
- ❑ 5. CEO/CFO
- ❑ 6. VP OF ______________________________
- ❑ 7. OTHER (PLEASE SPECIFY)____________________________________

3. What is the major business or institutional activity of your facility? (CHECK ONLY ONE)

- ❑ 1. HEAVY MANUFACTURING
- ❑ 2. LIGHT MANUFACTURING
- ❑ 3. WHOLESALE TRADE
- ❑ 4. RETAIL TRADE
- ❑ 5. GOVERNMENT
- ❑ 6. EDUCATION – RESEARCH
- ❑ 7. EDUCATION - GENERAL

- ❑ 8. HEALTH SERVICES
- ❑ 9. LODGING
- ❑ 10. AGRICULTURE
- ❑ 11. COMMERCIAL-OFFICE
- ❑ 12. COMMERCIAL-RETAIL
- ❑ 13. APARTMENT/CO-OP/CONDOMINIUM BUILDING
- ❑ 14. OTHER (PLEASE SPECIFY) ____

4. On average, what percent of your facility's total annual operating cost does your electricity bill represent?

- ❑ 1. LESS THAN 1%
- ❑ 2. BETWEEN 1% AND 3%
- ❑ 3. BETWEEN 4% AND 6%
- ❑ 4. BETWEEN 7% AND 10%
- ❑ 5. BETWEEN 11% AND 20%
- ❑ 6. GREATER THAN 20%
- ❑ 7. DON'T KNOW

5. How has this electricity component of your facility's total annual operating cost changed over the past 5 years?

- ❑ 1. INCREASED
- ❑ 2. DECREASED
- ❑ 3. NOT CHANGED AT ALL **(GOTO QUESTION 7)**
- ❑ 4. DON'T KNOW **(GOTO QUESTION 7)**

6. In what year did the largest change in the electricity component of your facility's total annual operating cost occur?

- ❑ 1. 1999
- ❑ 2. 2000
- ❑ 3. 2001
- ❑ 4. 2002
- ❑ 5. 2003
- ❑ 6. DON'T KNOW

7. Please rank the following time periods according to your facility's usage of electricity from highest to lowest use on a "normal-use" weekday (1=HIGHEST USE PERIOD, 4=LEAST USE PERIOD):

RANK	**TIME PERIODS**
_____	1. 8:00 A.M. – 11:59 A.M.
_____	2. 12 NOON – 4:59 P.M.
_____	3. 5:00 P.M. – 9:59 P.M.
_____	4. 10:00 P.M. – 7:59 A.M.

8. Does your facility's electricity usage fluctuate due to changes in temperature during the summer?

- ❑ 1. YES **(GOTO QUESTION 9)**
- ❑ 2. NO **(GOTO QUESTION 10)**

9. By how much does your facility's electricity usage fluctuate on very hot days in comparison to days with average temperatures during the summer?

- ❑ 1. LESS THAN 2%
- ❑ 2. BETWEEN 3% AND 6%
- ❑ 3. BETWEEN 7% AND 10%
- ❑ 4. MORE THAN 10%
- ❑ 5. DON'T KNOW

10. Over a 24-hour period, how many production shifts does your facility operate on a weekday?

- ❑ 1. ONE
- ❑ 2. TWO
- ❑ 3. THREE
- ❑ 4. MORE THAN THREE

11. Is a large portion of your electricity load comprised of batch production processes?

- ❑ 1. YES
- ❑ 2. NO
- ❑ 3. DOES NOT APPLY
- ❑ 4. DON'T KNOW

12. Over the past 5 years, which of the following months typically constitute those where a higher than average level of electricity is consumed due to increased business activity? (CHECK ALL THAT APPLY)

- ❑ 1. JANUARY

- ❑ 2. FEBRUARY
- ❑ 3. MARCH
- ❑ 4. APRIL
- ❑ 5. MAY
- ❑ 6. JUNE
- ❑ 7. JULY
- ❑ 8. AUGUST
- ❑ 9. SEPTEMBER
- ❑ 10. OCTOBER
- ❑ 11. NOVEMBER
- ❑ 12. DECEMBER
- ❑ 13. NONE

13. Over the past 5 years, which of the following weekdays typically constitute those where a higher than average level of electricity is consumed due to increased business activity? (CHECK ALL THAT APPLY)

- ❑ 1. MONDAY
- ❑ 2. TUESDAY
- ❑ 3. WEDNESDAY
- ❑ 4. THURSDAY
- ❑ 5. FRIDAY
- ❑ 6. NONE

The next section contains a series of questions concerning your participation in and opinions of Niagara Mohawk's SC-3A tariff rate that was re-designed and implemented back in November of 1998. This re-designed SC-3A rate will hereafter be referred to as SC-3A Retail Choice. Even if your facility chose the fixed-rate option, otherwise known as Option 2 in the tariff, which was only offered once, your answers to these questions are still very valuable to us.

14. Did your facility have any experience with the following time-varying rate structures before 1998? (CHECK ALL THAT APPLY)

- ❑ 1. HOURLY INTEGRATED PRICING PILOT (HIPP)
- ❑ 2. VOLUNTARY INTERRUPTIPLE PILOT PROGRAM (VIPP)
- ❑ 3. INTERRUPTIBLE RIDER (SC-3B OR SC-3C)
- ❑ 4. NONE OF THE ABOVE
- ❑ 5. DON'T KNOW

15. In general, how satisfied is your facility with the way Niagara Mohawk re-designed its SC-3A tariff rate in 1998?

COMPLETELY DISSATISFIED **1 2 3 4 5** COMPLETELY SATISIFIED

16. What is the primary issue that could haven been improved in the design of this rate offering? (CHOOSE ONLY ONE)

- ❑ 1. FIXED-RATE OPTION SHOULD NOT HAVE BEEN A "TAKE-OR-PAY" CONTRACT
- ❑ 2. FIXED-RATE OPTION SHOULD HAVE ALLOWED FOR A PROPORTION OF DEMAND TO BE NOMINATED NOT A FIXED MW VALUE
- ❑ 3. MORE INFORMATION SHOULD HAVE BEEN PROVIDED UP FRONT TO ASSIST MY FIRM IN MAKING A BETTER, MORE INFORMED DECISION
- ❑ 4. TOU-STYLE DEMAND CHARGE SHOULD BE REMOVED
- ❑ 5. THE VARIABLE RATE OPTION SHOULD HAVE COVERED ONLY CHANGES IN ELECTRICITY USAGE RELATIVE TO A BASELINE LEVEL OF LOAD
- ❑ 6. OTHER (PLEASE EXPLAIN) ________________________________
- ❑ 7. NONE

17. Just prior to beginning service on SC-3A Retail Choice, how well prepared was your facility to make the choice to nominate load for Option 2?

NOT AT ALL PREPARED **1 2 3 4 5** COMPLETELY PREPARED

18. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning forecasted energy prices for the period of 1998 - 2003?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

19. Just prior to beginning service on SC-3A Retail Choice, how familiar was your facility with commodity hedging methods and products?

NOT AT ALL FAMILIAR **1 2 3 4 5** COMPLETELY FAMILIAR

20. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning opportunities for procuring hedging arrangements from an entity other than Niagara Mohawk in order to reduce your price-risk exposure?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

21. Just prior to beginning service on SC-3A Retail Choice, how much experience did your facility have shopping for alternative electric commodity suppliers?

TOTALLY INEXPERIENCED **1 2 3 4 5** TOTALLY EXPERIENCED

22. Just prior to beginning service on SC-3A Retail Choice, how much information was your facility given by utilities, state agencies, retail suppliers or others concerning opportunities for procuring your electric commodity from an entity other than Niagara Mohawk?

NO INFORMATION **1 2 3 4 5** COMPLETE INFORMATION

23. Which of the following best characterizes your facility's current curtailment capability?

- ❑ 1. SHIFT ELECTRICITY USAGE FROM ONE TIME PERIOD TO ANOTHER **(GOTO QUESTION 25)**
- ❑ 2. FOREGO ELECTRICITY USAGE DURING A TIME PERIOD **(GOTO QUESTION 25)**
- ❑ 3. BOTH SHIFT AND FOREGO ELECTRICITY USAGE **(GOTO QUESTION 24)**
- ❑ 4. UNABLE TO CURTAIL LOAD **(GOTO QUESTION 31)**

24. According to your current curtailment capability, what percentage of your facility's expected reduction in electricity usage would be allocated to actions that shift this usage from one time period to another versus actions that forego the usage entirely? (THE PERCENTAGES SHOULD ADD TO 100)

% SHIFT: ____________________

% FOREGO: ____________________

25. Which of the following list of actions did your facility undertake to reduce electricity usage in response to high prices over the past 5 years? (CHECK ALL THAT APPLY)

- ❑ 1. NO ACTION WAS UNDERTAKEN
- ❑ 2. STARTED ONSITE OR EMERGENCY/BACKUP GENERATION
- ❑ 3. ASKED EMPLOYEES OR BUILDING OCCUPANTS TO REDUCE ELECTRICITY USE
- ❑ 4. TURNED OFF OR DIM LIGHTS
- ❑ 5. REDUCED OR HALTED USE OF AIR CONDITIONING
- ❑ 6. REDUCED OR HALTED USE OF REFRIGERATION
- ❑ 7. REDUCED OR HALTED USE OF WATER HEATING
- ❑ 8. REDUCED PLUG (OFFICE EQUIPMENT) LOADS
- ❑ 9. TURNED OFF OR LIMITED USE OF ELEVATORS AND/OR ESCALATORS
- ❑ 10. SHUT DOWN PLANT(S) OR BUILDING(S)
- ❑ 11. COMPLETELY HALTED MAJOR PRODUCTION PROCESSES

- ❑ 12. ALTERED MAJOR PRODUCTION PROCESSES
- ❑ 13. SHUT DOWN EQUIPMENT
- ❑ 14. OTHERS (PLEASE EXPLAIN)

____

26. If you indicated that your facility used on-site generation to reduce electricity usage during high priced periods, please estimate the amount of electricity demand, in MWs, this unit(s) would produce.

_______________ MW

27. During the weekday hours of 11 A.M. to 5 P.M., what must the average price for electricity have to be for your facility to begin reducing its electricity usage?

____________ $/MWh

28. When this indicated price is observed during the weekday hours of 11 A.M. to 5 P.M., on average how much of your electricity demand, both in average MWs and as a percent of your facility's electricity usage at the time, do you generally reduce?

____________ MW

____________ % OF ELECTRICITY USAGE AT THE TIME

29. During the weekday hours of 11 A.M to 5 P.M. when prices reach the level that you reduce and curtail electricity usage, how long does it take for your facility to resume full operation?

_____________ HOURS

30. Assume the average hourly price to purchase electricity on a weekday from 11 A.M. to 5 P.M. is $1000/MWh, how much of your facilities demand, in average MWs, would your facility expect to reduce?

____________ MW

31. Which of the following technologies did your facility have in place before Niagara Mohawk implemented SC-3A Retail Choice in November of 1998? (CHECK ALL THAT APPLY)

- ❑ 1. PROCESS/BUILDING AUTOMATION SYSTEMS
- ❑ 2. REAL-TIME ACCESS TO INTERVAL ELECTRICITY METER DATA
- ❑ 3. ENERGY INFORMATION SYSTEMS
- ❑ 4. CONTROL DEVICES ON SPECIFIC PROCESSES OR USES

- ❑ 5. PEAK-LOAD MANAGEMENT CONTROL DEVICES
- ❑ 6. ENERGY EFFICIENT LIGHTING
- ❑ 7. ENERGY EFFICIENT HVAC SYSTEMS OR EQUIPMENT
- ❑ 8. ENERGY EFFICIENT MOTORS, PUMPS, VFDs
- ❑ 9. NONE
- ❑ 10. DON'T KNOW

32. Since beginning service on SC-3A Retail Choice, did your facility make any additional investments in energy management and/or information systems that would help you respond better to hourly changes in price?

- ❑ 1. YES **(GOTO QUESTION 33)**
- ❑ 2. NO **(GOTO QUESTION 35)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 35)**

33. Since beginning service on SC-3A Retail Choice, in which of the following technologies did your facility invest? (CHECK ALL THAT APPLY)

- ❑ 1. PROCESS CONTROLS AND/OR AUTOMATION SYSTEMS
- ❑ 2. NEAR REAL-TIME ACCESS TO INTERVAL ELECTRICITY METER DATA (E.G. NMPC'S ENERGY CHECK ONLINE)
- ❑ 3. ENERGY INFORMATION SYSTEM
- ❑ 4. ENERGY MANAGEMENT CONTROL SYSTEM
- ❑ 5. DIRECT LOAD CONTROL DEVICES
- ❑ 6. PEAK-LOAD MANAGEMENT OR CONTROL DEVICES
- ❑ 7. ENERGY EFFICIENT LIGHTING
- ❑ 8. ENERGY EFFICIENT HVAC SYSTEMS
- ❑ 9. ENERGY EFFICIENT MOTORS AND/OR PUMPS

34. In which year did your facility first utilize most of these technologies or equipment to better respond to hourly changes in price?

- ❑ 1. 1999
- ❑ 2. 2000
- ❑ 3. 2001
- ❑ 4. 2002
- ❑ 5. 2003
- ❑ 6. DON'T KNOW

Electricity consumers in New York State are allowed to choose who supplies their electricity commodity. Next, we are going to ask you a series of questions concerning your interactions with these competitive electricity suppliers.

35. Did your facility nominate any of its peak demand under SC-3A's Retail Choice fixed-price electricity rate option, known as Option 2?

- ❑ 1. YES **(GOTO QUESTION 36)**
- ❑ 2. NO **(GOTO QUESTION 37)**

36. How satisfied is your facility with its decision to be served under the fixed-price electricity rate option (a.k.a. Option 2)?

COMPLETELY DISSATISFIED **1 2 3 4 5** COMPLETELY SATISIFIED

37. Hypothetically, if your facility were able to nominate a portion of your demand for an identically designed fixed-price electricity rate option that was provided by a competitive electricity supplier for the next five (5) years, how many MWs, on average, would you elect to have served for the summer on-peak and off-peak periods and the winter on-peak and off-peak periods?

SUMMER ON-PEAK ___________ SUMMER OFF-PEAK ________________

WINTER ON-PEAK ___________ WINTER OFF-PEAK ________________

38. At any time since November 1998, when SC-3A Retail Choice was first introduced, did your facility take service under any competitively offered rate options?

- ❑ 1. YES **(GOTO QUESTION 39)**
- ❑ 2. NO **(GOTO QUESTION 42)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 42)**

39. We would like to get a general sense of your facility's electric commodity rate and/or contract history since November 1998, when SC-3A Retail Choice was introduced. For each time period listed in the table below, please indicate which types of electric commodity rates or contracts most closely represent the ones your facility was on by checking the appropriate boxes. The summer months correspond to May, June, July, August and September, while the winter months represent October through December of the same year and then January through April of the following year.

Time Period	**Flat Rate**	**Time-Of-Use Rate**	**Price Index**	**Volumetric Collar**	**Other**	**SC-3A**
Winter 1998 - 1999						
Summer 1999						
Winter 1999 - 2000						
Summer 2000						
Winter 2000 - 2001						
Summer 2001						
Winter 2001 – 2002						
Summer 2002						
Winter 2002 – 2003						
Summer 2003						

40. What were the reasons your facility chose to take service under a competitively offered rate option? (CHECK ALL THAT APPLY)

- ❑ 1. SC3-A PRICES EXPECTED TO BE TOO VOLATILE
- ❑ 2. NO LONGER INTERESTED IN RATE WHERE PRICES VARIED EACH HOUR
- ❑ 3. FOUND WE WERE UNABLE TO ADJUST LOAD IN RESPONSE TO VARYING PRICES
- ❑ 4. RECEIVED FINANCIALLY ATTRACTIVE OFFER FROM A COMPETITIVE SUPPLIER
- ❑ 5. DISCOVERED THAT ADJUSTING LOAD IN RESPONSE TO VARYING PRICES WAS NOT COST-EFFECTIVE
- ❑ 6. WANTED MORE PREDICTABLE RATE STRUCTURE
- ❑ 7. THE TERMS OF OPTION 2 WERE UNACCEPTABLE
- ❑ 8. WISHED TO TAKE ADVANTAGE OF CUSTOMER SERVICE BACK-OUT CREDIT
- ❑ 9. OTHER (PLEASE EXPLAIN) ____

41. We would also like to get a general sense of your facility's history with financial hedge products since SC-3A Retail Choice was introduced in November 1998. For each time period listed in the table below, please indicate which types of hedge products most closely represent the ones your facility had purchased by checking the appropriate boxes. The summer months correspond to May, June, July, August and September, while the winter months represent October through December of the same year and then January through April of the following year.

Time Period	Price Collar	Price Cap	Financial Swap	Other	None
Winter 1998 - 1999					
Summer 1999					
Winter 1999 - 2000					
Summer 2000					
Winter 2000 - 2001					
Summer 2001					
Winter 2001 – 2002					
Summer 2002					
Winter 2002 – 2003					
Summer 2003					

We would now like to ask you some questions concerning the demand response programs currently offered in New York State.

42. Has your facility ever registered for the Emergency Demand Response Program, commonly referred to as EDRP?

- ❑ 1. YES **(GOTO QUESTION 43)**
- ❑ 2. NO **(GOTO QUESTION 45)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 45)**

43. In which years did your facility reduce load in response to a declared EDRP event? (CHECK ALL THAT APPLY)

- ❑ 1. 2001
- ❑ 2. 2002
- ❑ 3. 2003

44. Assume the hourly price to purchase electricity from 11 A.M. to 5 P.M. were $500/MWh and an EDRP event was declared during this time period paying you an additional $500/MWh, on average how much of your demand, in MWs, would your facility expect to reduce?

_______________________ MWs

45. Has your facility ever registered for the Day-Ahead Demand Response Program, commonly referred to as DADRP?

- ❑ 1. YES **(GOTO QUESTION 46)**
- ❑ 2. NO **(GOTO QUESTION 47)**
- ❑ 3. DON'T KNOW **(GOTO QUESTION 47)**

46. In which years did your facility submit a bid to curtail to the DADRP? (CHECK ALL THAT APPLY)

- ❑ 1. 2001
- ❑ 2. 2002
- ❑ 3. 2003
- ❑ 4. NONE

SKIP TO QUESTION 48

47. Which one of the following best describes the primary reason your facility chose to not register for the DADRP?

- ❑ 1. POTENTIAL BENEFITS DON'T JUSTIFY THE RISKS
- ❑ 2. PENALTY IS TOO SEVERE
- ❑ 3. PAYMENTS ARE TOO LOW
- ❑ 4. UNABLE TO SHIFT USAGE
- ❑ 5. INADEQUATE KNOWLEDGE OF DADRP REQUIREMENTS
- ❑ 6. INABILITY TO USE DIESEL GENERATORS
- ❑ 7. OTHER ____________________________

- [ ] 8. DON'T KNOW

48. How comfortable are you with creating a load curtailment plan to meet a specific MW reduction target?

    NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

49. How comfortable are you with monitoring the NYISO's Day-Ahead market electricity prices to determine whether and if to bid?

    NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

50. How comfortable are you with determining at what price to bid?

    NOT COMFORTABLE **1 2 3 4 5** VERY COMFORTABLE

51. If you were to submit a bid to curtail electricity during the weekday hours of 11 A.M to 5 P.M. through the DADRP, what is the minimum price, in $/MWh, at which you would offer to reduce electricity?

    ____________________ $/MWh

52. On average, how much of your electricity demand, in MWs, would your facility offer to reduce at this price during this period?

    ____________________ MWs

53. Has your facility ever registered for the ICAP Special Case Resource program, commonly referred to as SCR?

    - [ ] 1. YES **(GOTO QUESTION 54)**
    - [ ] 2. NO **(GOTO QUESTION 55)**
    - [ ] 3. DON'T KNOW **(GOTO QUESTION 55)**

54. In which years did your facility sell its load curtailment or on-site generation output as a capacity resource in the ICAP/SCR program? (CHECK ALL THAT APPLY)

    - [ ] 1. 2001
    - [ ] 2. 2002
    - [ ] 3. 2003

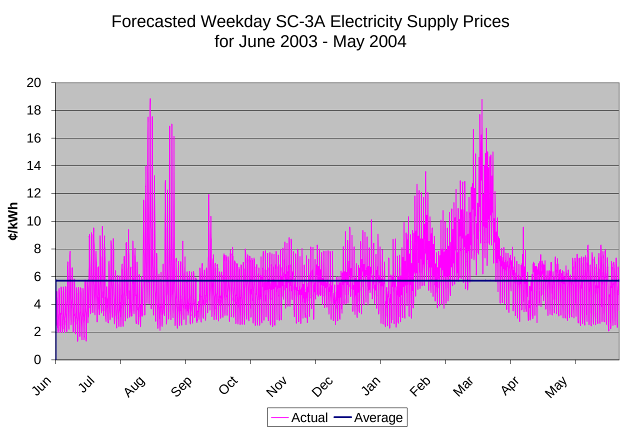
55. Would you be willing to participate in a follow-up interview within the next three weeks? If so, please indicate below. Interviews, which will last roughly 20 – 25 minutes, will be conducted over the phone with one of our staff members. If you indicate "Yes" below, then you will be entered into a drawing to win either a digital video camera or a weekend getaway to Niagara Falls each valued at $450,

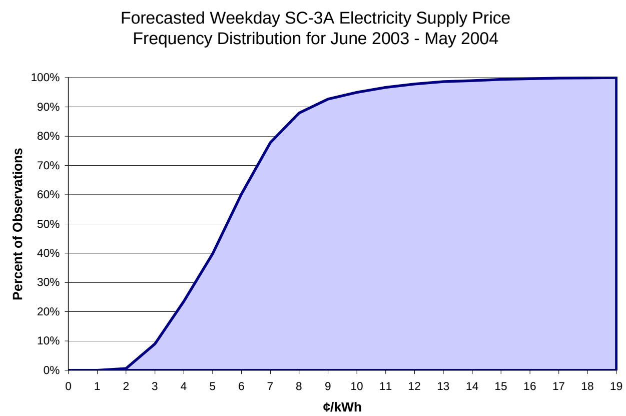
unless you subsequently refuse to schedule and complete the interview. The odds of winning are 1:50.

- ❑ 1. YES, I WOULD BE WILLING TO PARTICIPATE IN A FOLLOW-UP INTERVIEW
- ❑ 2. NO, I WOULD NOT LIKE TO PARTICIPATE IN ANY FOLLOW-UP INTERVIEWS

This is the last section of the survey; it takes about 15 minutes to complete and then you are finished.

In this section, we ask you to make a series of choices among different electricity hedging contracts that vary in how much price variation you are exposed to and the hedging premium you pay. In each case, you can elect to pay no hedging premium and face market-based hourly electricity prices.
To characterize the decision environment, suppose that day-ahead hourly electricity prices under Option 1 of SC-3A for June 2003 through May 2004 are forecasted to average around 5.7 ¢/kWh, but are subject to variation illustrated in the figures below. While generally below 10 ¢/kWh, prices may climb into the 15 – 20 ¢/kWh range during one or more days, usually, but not always in the summers, and have historically reached as high as 100 ¢/kWh for short periods.





In each of the following 19 questions, you are going to be shown a set of four (4) hedge contracts, each containing different levels of five hedge features, as follows:

1. The amount of your load the hedge contract covers;
2. The hours of the weekday covered by the hedge contract;
3. The months of the year covered by the hedge contract;
4. The Hedge design; and
5. The Hedge price and premium.

In each choice, select one of the hedge contracts, or the SC-3A unhedged alternative. Please indicate your choice by checking the appropriate box. It is very important that you select one choice for each of the 19 questions. An example pricing plan alternative is provided on the next page

Explanation of Contract Features and an example alternative

	Hedge Load	Covered Hours	Covered Months	Hedge Method	Hedge Price
Hedge 1	50%	12 Noon - 10 PM	Jun - Aug and Dec - Feb	Capped Price	7¢/kWh @ 10%

<u>Hedged Load</u>

- **The percentage of maximum demand that the hedge contract will cover**
- In the sample hedge contract above, 50% of your organization's maximum demand will be covered under the hedge.

<u>Covered Hours</u>

- **The hours of the weekday covered by the hedge contract. In the hours not covered, the SC-3A pricing plan applies.**
- In the sample hedge contract above, the hedge would cover electricity usage during the hours of 12 Noon through 10 PM.

<u>Covered Months</u>

- **The months of the year covered by the hedge contract. In all months not covered, the SC-3A pricing plan applies.**
- In the sample hedge contract above, the hedge would cover electricity usage during the months of June through August and December through February.

<u>Hedge Method</u>

- **The type of pricing method used in the hedge, either a *Capped Price* or *Average Price*. A *Capped Price* hedge limits the price your organization would pay for its electricity usage to always be below the indicated price threshold. An average price hedge effectively results in paying a flat rate.**
- In the sample hedge contract above, the hedge uses a Capped Price.

<u>Hedge Price</u>

- **The price at which the electric commodity is purchased and the total cost of the hedge in terms of the percent of your monthly SC-3A electricity bill.**
- Because the hedge method in the example above is a Capped Price, the Hedge Price of 7 ¢/kWh represents the highest price for electricity usage your organization would have to pay. If the hedge method were an "Average Price", then your organization would pay 7 ¢/kWh for the all of its electricity usage covered under the hedge contract. To purchase this hedge, it would cost your organization 10% of its monthly SC-3A electricity bill.

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 1

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	100%	75%	25%	
Covered Hours	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	Jun - Aug	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	8¢/kWh @ 5%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 2

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	100%	25%	
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 10 PM	6 AM - 12 Noon	
Covered Months	All Year	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Average Price	Capped Price	Capped Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 3

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	100%	25%	50%	
Covered Hours	6 AM - 12 Noon	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	
Covered Months	All Year	Jun - Aug	Jun - Aug and Dec - Feb	Dec- Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Capped Price	Average Price	Average Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 4

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	50%	25%	
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec- Feb	Jun - Aug	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Capped Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	9¢/kWh @ 3%	8¢/kWh @ 5%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 5

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	50%	25%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 6 PM	12 Noon - 10 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug	Jun - Aug and Dec - Feb	All Year	Dec - Feb	
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	9¢/kWh @ 3%	8¢/kWh @ 5%	6¢/kWh @ 15%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 6

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	50%	100%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	12 Noon - 10 PM	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 7

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	25%	100%	
Covered Hours	12 Noon - 6 PM	6 AM - 12 Noon	12 Noon - 10 PM	6 AM - 10 PM	
Covered Months	Jun - Aug	All Year	Dec - Feb	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	7¢/kWh @ 10%	8¢/kWh @ 5%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 8

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	50%	100%	25%	
Covered Hours	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	Jun - Aug	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 9

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	75%	25%	50%	
Covered Hours	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 10 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Jun - Aug and Dec - Feb	All Year	Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Capped Price	Average Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 10

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	50%	100%	
Covered Hours	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Average Price	Capped Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	6¢/kWh @ 15%	9¢/kWh @ 3%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 11

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	100%	50%	25%	75%	
Covered Hours	6 AM - 10 PM	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	All Year	Dec - Feb	Jun - Aug and Dec - Feb	Jun - Aug	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Capped Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 12

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	100%	75%	50%	
Covered Hours	12 Noon - 10 PM	6 AM - 12 Noon	12 Noon - 6 PM	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	All Year	Dec - Feb	Jun - Aug	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	8¢/kWh @ 5%	7¢/kWh @ 10%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 13

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	25%	100%	75%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	6 AM - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	All Year	Dec - Feb	Jun - Aug	
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	6¢/kWh @ 15%	7¢/kWh @ 10%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 14

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	25%	50%	100%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 10 PM	6 AM - 12 Noon	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	All Year	Dec - Feb	Jun - Aug	Jun - Aug and Dec - Feb	
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	9¢/kWh @ 3%	6¢/kWh @ 15%	7¢/kWh @ 10%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 15

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	100%	25%	50%	
Covered Hours	6 AM - 12 Noon	6 AM - 10 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Dec - Feb	All Year	Jun - Aug	I wouldn't purchase any of these hedges.
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	8¢/kWh @ 5%	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 16

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	25%	75%	100%	50%	
Covered Hours	6 AM - 12 Noon	12 Noon - 6 PM	6 AM - 10 PM	12 Noon - 10 PM	
Covered Months	Dec - Feb	All Year	Jun - Aug	Jun - Aug and Dec - Feb	I wouldn't purchase any of these hedges.
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	9¢/kWh @ 3%	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 17

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	25%	100%	75%	I wouldn't purchase any of these hedges.
Covered Hours	6 AM - 10 PM	6 AM - 12 PM	12 Noon - 6 PM	12 Noon - 10 PM	
Covered Months	Jun - Aug and Dec - Feb	Jun - Aug	Dec - Feb	All Year	
Hedge Method	Capped Price	Average Price	Average Price	Capped Price	
Hedge Load	8¢/kWh @ 5%	7¢/kWh @ 10%	6¢/kWh @ 15%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 18

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	50%	100%	25%	75%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 6 PM	6 AM - 12 PM	12 Noon - 10 PM	6 AM - 10 PM	
Covered Months	All Year	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	
Hedge Method	Average Price	Capped Price	Capped Price	Average Price	
Hedge Load	7¢/kWh @ 10%	6¢/kWh @ 15%	8¢/kWh @ 5%	9¢/kWh @ 3%	
Check only one choice	☐	☐	☐	☐	☐

Which of these 4 Hedge Contracts would you choose, if any?

Choice Set 19

	Hedge 1	Hedge 2	Hedge 3	Hedge 4	None
Hedge Load	75%	25%	100%	50%	I wouldn't purchase any of these hedges.
Covered Hours	12 Noon - 10 PM	6 AM - 10 PM	12 Noon - 6 PM	6 AM - 12 Noon	
Covered Months	Jun - Aug	Dec - Feb	Jun - Aug and Dec - Feb	All Year	
Hedge Method	Average Price	Capped Price	Average Price	Average Price	
Hedge Load	7¢/kWh @ 10%	9¢/kWh @ 3%	8¢/kWh @ 5%	6¢/kWh @ 15%	
Check only one choice	☐	☐	☐	☐	☐

Appendix C: Hypotheses for NMPC SC-3A Demand Modeling

No.	Null Hypothesis	Testing Method	Data Needed	Survey Question
	Changes in Response due to Price Timeline			
1.1	No structural change in customer responsiveness across introduction of NYISO prices, summer 2000 NYISO price spikes, and introduction of PRL Programs (price regimes)	Chow Test or Dummy Var in regression	NMPC price data	
	Firmographic Effects			
2.1	Degree of responsiveness (elasticity) is unaffected by time of peak demand	Demand Elasticity Model (or ANOV)	Define peak demand from meter data and survey	7
2.2	Degree of responsiveness (elasticity) is unaffected if large industrial or small commercial classification	Demand Elasticity Model (or ANOV)	Define type and size from survey and meter data	3
2.3	Degree of responsiveness (elasticity) is unaffected by level of load factor	Demand Elasticity Model (or ANOV)	Define load factor from meter data	
2.4	Degree of responsiveness (elasticity) is unaffected if customer's electricity costs are a large percentage of total costs or not	Demand Elasticity Model (or ANOV)	Electricity costs identified via survey	3
2.5	Degree of responsiveness (elasticity) is unaffected if customer has multiple shifts or not	Demand Elasticity Model (or ANOV)	Number of shifts identified via survey	10
2.6	Degree of responsiveness (elasticity) is unaffected if customer has high degree of production flexibility or not	Demand Elasticity Model (or ANOV)	Production flexibility identified via survey	Removed
2.7	Degree of responsiveness (elasticity) is unaffected if customer has periods of high business activity or not	Demand Elasticity Model (or ANOV)	Production schedule identified via survey	12, 13
2.8	Type of response (forego vs. shift) is unaffected by Business classification	Chi-Square (or ANOV if response type is continuous)	Define type of business from survey data. Assess response characteristic from demand model.	3
	Method of Response			
3.1	Proportion of customer's using on-site generation vs. other methods of response	Descriptive Statistic	On-site generation identified via survey	25
3.2	Degree of responsiveness (elasticity) is unaffected by use of on-site generation vs. other methods of response	Demand Elasticity Model (or ANOV)	On-site generation identified via survey	25
3.3	Degree of responsiveness (elasticity) is unaffected by investments in load-shifting technology or not	Demand Elasticity Model (or ANOV)	Load-shifting technology investment identified via survey	31, 33
3.4	Degree of responsiveness (elasticity) is unaffected by process type (batch vs. continuous)	Demand Elasticity Model (or ANOV)	Process type identified via survey	11
	Experience with HIPP			
4.1	Proportion of people choosing Option 1 vs. Option 2 is unaffected by prior experience with HIPP	Chi-Square	Prior experience w/ HIPP and choice of Option 1 or 2 identified via survey	14
4.2	Degree of responsiveness (elasticity) is unaffected by prior experience with HIPP	Demand Elasticity Model (or ANOV)	Prior experience w/ HIPP and choice of Option 1 or 2 identified via survey	14
4.3	Degree of responsiveness (elasticity) is unaffected by the number of years on an RTP (HIPP/SC-3A) rate	Demand Elasticity Model (or ANOV)	Number of years on an RTP rate identified via survey	14
	Response as a Function of Prices			
5.1	Prices must reach a self-reported or analytically determined threshold before significant response is undertaken	Descriptive Statistic	Price threshold identified via survey or analytically from the data	27
5.2	Prices must reach a self-reported or analytically determined percentage above average before significant response is undertaken	Descriptive Statistic	Percentage price increase identified via survey or analytically from the data	Removed
5.3	Degree of responsiveness (elasticity) is unaffected by the voltage level	Demand Elasticity Model (or ANOV)	Voltage level based on NMPC data	
5.4	Degree of responsiveness (elasticity) is unaffected by the location in the state	Demand Elasticity Model (or ANOV)	Location in the state based on NMPC data	
	Effects of Hedging Contracts			
6.1	Degree of responsiveness (elasticity) is unaffected by holding a hedge or not	Demand Elasticity Model (or ANOV)	Hedge purchase identified via survey	39, 41
6.2	There is no difference in the number of people choosing between Option 1 vs. Hedged Service (Option 2 or an independent contractor) at inception of SC-3A	Descriptive Statistic	Hedge purchase identified via survey	39, 41
6.3	The difference in the number of people choosing to purchase a hedge contract is unaffected by the "three price regimes"	Chow Test or Dummy Var in regression	Hedge purchase identified via survey	39, 41
6.4	Degree of responsiveness (elasticity) is unaffected by the proportion of load hedged	Demand Elasticity Model (or ANOV)	Hedge purchase identified via survey	39, 41
	Interaction between RTP and PRL Programs			
7.1	The proportion of people choosing to participate in a NYISO PRL program is unaffected by the choice to hedge or not	Chi-Square	PRL program participation identified via survey	39, 41, 42, 45, 53
7.2	The proportion of customers chosing to participate in DADRP is unaffected by degree of responsiveness (elasticity)	Chi-Sqyare	PRL program participation identified via survey	45
7.3	The proportion of customers chosing to participate in ICAP/SCR is unaffected by degree of responsiveness (elasticity)	Chi-Squate	PRL program participation identified via survey	53
7.4	The proportion of customers chosing to participate in EDRP is unaffected by degree of responsiveness (elasticity)	Chi-Squate	PRL program participation identified via survey	42

Appendix D: Economic Theory of Discrete Choice Models

The modeling of the stated preferences of customers for hedging load can be accomplished within a random utility formulation. This was facilitated in Part II of the customer survey by having respondents select individual choices from choice sets involving choices among four hedge products with different values for five features and a "no program" alternative.[1] Accordingly, we model this choice situation as though the i^{th} customer is faced with J choices, and the utility of the choice j is given by:

(1) $U_{ij} = \beta' Z_{ij} + \varepsilon_{ij}$.

where
U_{ij} = the utility of customer i making choice j utility;
Z_{ij} = is a vector of program features;
β' = vector of parameters to be estimated; and
ε_{ij} = an error term.

If the customer chooses program feature j, then it is assumed that U_{ij} is the maximum of the utilities for all the J alternatives. The statistical model is driven by the probability that choice j is made:

(2) Prob $[U_{ij} > U_{ik}]$ for all $k \neq j$.

This indicates the probability that the utility of choice j for individual i is greater than the utility of any other choice k.

To make this model operational, we must make an assumption about the distribution of disturbances, ε_{ij}. Following McFadden (1973) and Greene (1990), we let Y_i be a random variable for the choice made. It can be shown that if (and only if) the disturbances are independent and identically distributed according to a Weibull distribution,

(3) $F(\varepsilon_{ij}) = \exp(-e^{-\varepsilon ij})$,

then, we can express the probability of choice j by individual i (Prob $[Y_i = j]$) as:

(4) Prob $[Y_i = j] = \exp[\beta' Z_{ij}] / \{\sum_j [\exp \beta' Z_{ij}]\}$,

is called the conditional logit model. As in the case of the binary logit model, this conditional logit model is estimated by the method of maximum likelihood but uses the SAS procedure PROC PHREG due to its ability to handle tied data (Allison, 1999).

[1] The conjoint survey is included in Appendix B. The features used in the choice sets represent the major characteristics of a hedge contract. The range in values used in creating the choice sets reflect those ascertained by the research team as feasible, given the team's experience in this area and through discussions with retail suppliers offering such products.

Appendix E: Methods for Estimating Response in Electricity Usage to Real Time Prices

Introduction

This appendix provides a detailed discussion of the economic model used to estimate Niagara Mohawk Power Company's industrial and commercial customers' response to electricity prices. Based on these customers' circumstances, electricity use is modeled as the derived demand for electricity as an input into the productive and business processes of firms. Consequently, the appropriate economic specification is to characterize how firms make decisions on how much electricity to use to minimize their cost of production. Following well-established conventions, electricity is portrayed as two inputs differentiated by the time in which it is deployed; peak or off-peak. This specification poses several conceptual issues that need to be resolved in using real time pricing (RTP) data to estimate price responsiveness, which are discussed in some detail. The final model used to estimate price elasticities, referred to as the Constant Elasticity of Substitution (CES), is a highly structured and theoretically consistent representation of the trade-offs made by firms between peak and off-peak electricity usage. The CES model also provides a means for quantifying how firms alter the relative use of electricity in peak and off-peak periods.[2]

We selected the CES specification because it provided a tractable means for estimating substitution elasticities given time, resource, and data availability constraints. But, the CES model approach also imposes certain rigidities on assumed customer behavior; most notably that shifting opportunities are limited to the day's peak and off-peak periods and that the elasticity of substitution is constant. These assumptions may not fully reflect how some customers actually respond. Thus, we describe two alternative, more complex specifications of the demand model that allow customers to shift usage to the subsequent day (see Attachment B) or allow elasticities to vary with the nominal level of the change (see Attachment A). These models provide a means to test additional hypotheses about factors affecting customers' price responsiveness and could represent useful areas for additional research and analysis of the NMPC RTP customer database.

Finally, we discuss an approach that can be used to characterize different types of customer demand response behavior. The survey administered to SC-3A customers revealed three distinct response behaviors: load shifting, foregoing discretionary usage, and conservation. If customers shift their activity and usage from the peak to the off-peak period, holding output constant, then that behavior is fully captured by the CES model specifications, which accurately characterizes the response in terms of reduced on-peak usage. However, if customers forego "discretionary" usage during the high priced (peak) period (e.g., by raising thermostat set-points or turning off some lights) and still hold output constant, then the CES model does not fully capture the resulting impact in reduced peak consumption. While the ratio of peak to off-peak usage changes (declines),

[2] The greater the ability of a firm to adjust output to accommodate relative electricity prices, the larger its reduction in peak usage when SC-3A day-ahead prices increase.

the estimated substitution elasticity underestimates the actual peak usage reductions. Finally, "conservation," defined as an equal proportional reduction in both peak and off-peak usage during days of high prices, yields a substitution elasticity of zero, which again results in the underestimation of actual peak reductions. Following Patrick (1990), we developed a Load Response Characterization (LRC) model that determines whether customers' behavior is most consistent with load shifting, foregoing, or conservation. We take results from the LRC model to develop and apply an adjustment factor to correct for the underestimation of peak load reduction in estimating the aggregate demand response potential of NMPC SC-3A customers.

The Electricity Demand Model

Our focus is on the use and allocation of electricity inputs by industrial and commercial customers and the quantification of their electricity usage response to changes in price. Therefore, the most appropriate theoretical economic model should attempt to describe how firms maximize profit, or equivalently, how they minimize cost for producing a given level of output. Further, this economic problem involves a three-level profit or cost function, because the underlying production function is assumed be separable in electricity usage.[3] The practical implication of separability in production is that choice of cost minimizing input levels (peak and off-peak electricity use) within any sub-function (the total electricity usage relationship) depends only on prices of those inputs. Thus input demands and price response elasticities can be derived from the sub-function alone, without explicit knowledge of the overall output of the firm or its use of other inputs.

At the first level of cost minimization, we allocate weekday electricity usage between time periods during the day in which electricity prices differ, and/or the values of electricity to the firm differ. The second level involves allocating monthly usage between weekdays and weekends, and the third determines overall electricity expenditures as a proportion of total costs, reflecting the relative demand for electricity in relation to all other inputs in the firm's production process.

Given this theoretical specification, the corresponding empirical approach for estimating customers' response to changes in electricity prices would be to estimate all three levels of electricity demand within the same modeling framework. This would provide an in-depth characterization of the role and value of electricity in the firm's operation. Unfortunately, this is seldom possible. Estimating the latter two stages requires data on the firm's output level, its usage of inputs other than electricity, and output and input

[3] For a production function or utility function to be weakly separable in any partition of its arguments, the marginal rate of substitution between any two inputs or goods in a separable subset is independent of all inputs or goods that are not in the subset (Chambers, 1988, pp. 45-46). In other words, any function in n variables, $f(x) = F(x_1, \ldots, x_n)$, that is separable in a partition x^1 through x^m, where x^i is a vector representing a subset of the n variables, can be written as $f(x) = F(f^1(x^1), \ldots, f^n(x^n))$. Each of the sub-functions can be treated as an aggregate input or consumption bundle—essentially a production or utility function in and of itself. Therefore, it is legitimate to think of production or consumption occurring in two steps. To use the example of a production function, inputs in the sub-vector are combined to create the aggregate inputs in the first step. In the second step, these aggregate inputs are used to produce the output via the macro production function.

prices available at the same level of granularity as electricity prices (i.e., hourly values). Even if such data were readily available, customers would be reluctant to provide detailed production and price data, given confidentiality and competitiveness concerns.

The alternative is to use this theoretical model of derived factor demand as a general guide for specifying the empirical model, which characterizes the first stage of the model (i.e., the choice of the level of peak and off-peak electricity usage given prevailing prices). Moreover, survey information collected from firms provides a means for expanding the characterization, and identifying important drivers that distinguish customers according to their inclination to respond to price changes. This approach is consistent with the preponderance of past empirical work on modeling firm response to varying electricity prices.[4]

Defining the Electricity Commodity

In the literature, it is generally agreed that the appropriate representation of how customers make peak and off-peak electricity usage decisions is as a firm's factor demand system (Patrick, 1990; Braithwait, 2000). However, developing the appropriate empirical specification for examining hourly pricing programs for retail electricity customers is challenging because of the subjectivity in defining the electricity peak and off-peak commodities. The issue is essentially the same for examining TOU and RTP rates, but they are normally dealt with differently because of the way in which the data are generated. TOU service involves a price schedule, with different prices for specified, mutually exclusive and exhaustive time periods. Consequently data for TOU customers involve usage data only for the collective peak hours (in a month, typically) and the corresponding off-peak hours. TOU prices differ between the peak and off-peak periods, but these prices are the same for all days in the month.[5] Conversely, data from RTP programs include hourly usage data and price data that differ by day and hour.

In the case of TOU usage data, defining the energy commodities by the peak and off-peak usage aggregates is straightforward, because the TOU rate creates that distinction. Customers face a separate price for each of these two electricity commodities, defined by the peak and off-peak periods, and the price is constant for each commodity. This is

[4] This basic model is conceptually similar to the consumer demand model discussed by Braithwait (2000) in a recent study of residential TOU rates in New Jersey. His data came from a pilot study implemented by GPU Energy in summer 1997. In that study, Braithwait begins the theoretical analysis with the maximization of a three-level indirect utility function, which is assumed separable in electricity consumption. At the first level, weekday electricity usage is allocated between time periods in which electricity prices differ. The second level allocates monthly usage between weekdays and weekends, while the third determines overall electricity expenditures as a proportion of income, reflecting the relative demand for electricity in relation to all other goods. Empirically, he focuses exclusively on the first stage, and goes on to derive demand functions using both the constant elasticity of substitution (CES) and Generalized Leontief (GL) forms. In an earlier paper, Caves, *et al*. (1984) estimate a demand model that includes all three stages of electricity demand based on data from five experimental implementations of residential TOU rates in the United States. It is perhaps the only study that looks at all three stages of electricity demand, and one of only a handful of studies that consider more than just the within-day energy demand (see also Herriges *et al*. 1993; and Schwarz et al., 2002).

[5] Prices may change from season to season.

consistent with an economist's notion of distinct commodities: their prices differ so they have different values to the firm. However, with TOU data, there is no price variation across days against which to measure demand response for any individual customer. To introduce price variability, most studies of TOU rates have pooled data for different customers participating in several separate TOU rates, or data are pooled across several treatments for a given rate experiment (Patrick, 1990; Braithwait, 2000; Caves et al, 1984).[6] In other studies, different TOU treatments were implemented to provide price variations representative customers are defined for the separate programs (Charles River, 2004).

Data for RTP customers is almost too extensive. If one truly believes that industrial and commercial RTP customers can "load" follow on an hourly basis and adjust usage to different hourly prices, then each hour's electricity use is indeed one of 24 distinct commodities. Herriges et al. (1993) adopted this strategy in analyzing Niagara Mohawk Power Corporation's initial RTP pilot program, called Hourly Integrated Pricing Program (HIPP), where the price change in any hour causes usage shifts in other hours of the same day according to an Allen partial elasticity of substitution derived from a nested CES model. This model accounts for inter-day shifts as well, which is important when firms respond by moving production to another day.

Generally however, analysts have resorted to creating aggregate electricity commodities by grouping hours of the day. For example, in an effort to identify demand elasticities for hourly electricity commodities that are identically priced, Caves *et al*. (1987) identify six separate commodities for customers facing a six-hour peak pricing period, where two three-hour segments of the peak period are separated by a single hour. These peak hours are divided into two separate commodities—one two-hour commodity and one four-hour commodity. The remaining hours are aggregated into four separate commodities; all are priced the same. They argue that this sub-aggregation of the peak is needed to examine the existence of needle peaking (e.g. large increases in consumption in hours adjacent to the peak). Similarly, Patrick (1990) describes several analyses conducted on pilot data from TOU pilots conducted in the 1970s, and utilizes the CES formulation in his study of these program results.

Utilizing a fully disaggregated model, like the one adopted by Herriges *et al*. (1993), with 24-separately priced commodities, is advantageous in that it does not impose any specific structure on behavior, and therefore allows for a variety of responses that reflect different customer circumstances. Moreover, it provides a means for tracing exactly how the load shape is adjusted, which is important if the response to high prices in some hours results in shifting that peak to another hour, creating a needle peak that exceed the typical peak hour's usage, instead of spreading it out over several hours, or foregoing consumption

[6] Braithwait (2000) was able to examine price responsiveness of customers in two different ways because of the nature of the residential TOU rate. The first was to estimate substitution elasticities between peak and off-peak periods. He assumed that for any given day, there were only two electricity commodities. His second approach was to estimate substitution elasticities among three separate electricity commodities—usage during peak, shoulder, and off-peak periods. As one might expect, the substitution elasticities between peak and shoulder periods and shoulder and off-peak were lower than for peak to off-peak periods.

altogether. As part of this Appendix (see Attachment B), we outline this model as a guide for future research. However, such an elaborate specification was beyond the resources of this project.

In this study, we employed a simpler, single-stage constant elasticity of substitution (CES) model to analyze the behavior of SC-3A customers, utilizing two aggregate commodities, peak and off-peak consumption of electricity. The model allows price responsiveness to differ by the size of the price differences, but not by the nominal level of the prices themselves (thus the constant designation). To specify the CES model, we split the day into two demand periods—a high priced period and a low priced period. The "demand inducing" price for each commodity is assumed to be the average hourly price in the relevant block of hours. By interpreting the data in this way, we are able to study the demand response behavior of firms between "peak" and "off-peak" times in a consistent fashion. But, how are the peak and off-peak defined? To qualify as distinct peak and off-peak commodities, the day must be divided so that the resulting consumption aggregates support the firm's desired daily output, that could be substituted for one another to achieve that output, and that result in commodity prices that are sufficient in level to induce such substitution. While all SC-3A customers effectively face the same prices, those prices vary in their daily pattern for summer to winter, and even among weekdays in the same season. However, there are distinct delineations; high prices predominantly occur in consecutive afternoon hours, the timing and duration of which are the main sources of variation.[7] This suggests that the peak should comprise the afternoon hours, but exactly which depends on the pattern and level of the prices themselves.

The model was estimated for several alternative peak periods that differ in length and the time period they cover, to allow the data to determine the extent to which firms view electricity as a distinct hourly commodity or as one that involves hourly aggregates.[8]

We explored several alternative definitions of the peak period, which were defined as the hours between Noon to 5:00 p.m., 1:00 p.m. to 5:00 p.m., and 2:00 p.m. to 5:00 p.m.; each specification is used to estimate the demand equations, as discussed below.

---

[7] SC-3A prices are differentiated by NYISO zone and by the delivery transmission level (transmission, primary, secondary). The latter amount to differences in the loss factor applied to NYISO prices. The main zonal price difference is for the Capital region, which exhibits somewhat higher prices than the rest of the NMPC service territory. However, because in the CES formulation, the substitution elasticity depends on relative price changes, and not on their nominal level, customers in this region can be pooled with those in other zones in model estimation.

[8] Rather than specifying this peak period for the same hours of the day regardless of prices, an alternative would be to define a "dynamic" peak period, whereby the definition of peak varies each day. This would be accomplished by defining a peak period of a specified length, say three-hours for example, as the three hours of the afternoon where the consecutive three-hour average prices are the highest. By defining the customer "peak" in this way, we assume that customers are willing to reduce load for a three-hour period every day, but those three hours are determined to be those consecutive with the highest average prices. This seems a reasonable alternative behavioral assumption to test since the firms are given the 24-hour prices a day in advance, but one that was beyond the scope of this study.

The Single-Stage CES Model Specification

To begin the model development, we define a firm's production function that is separable in its peak and of-peak electricity inputs as:

(1) $Q = F(x_1, x_2,\ldots,x_n , q(k_p, k_o))$,

where Q is output of the firm, x_i are inputs other than electricity (labor, materials, etc.) and k_p and k_o are aggregate electricity use (kWh) in peak and off-peak periods, respectively. Assuming that electricity use is separable from other inputs, and employing the CES specification of the production relationship, we can write the electricity sub-function as:

(2) $q = [\ \delta\ (k_p)^{-\rho} + (1-\delta)\ (k_o)^{-\rho}\ ]^{-1/\rho}$

In this function, q is an aggregate electricity input that exhibits constant returns to scale (Moroney, 1972; and Ferguson, 1969). The parameter δ reflects the natural peak kWh intensity of production. The parameter ρ measures the transformation of the elasticity of substitution between peak and off-peak electricity use, where $\sigma = 1/(1 + \rho)$.[9] This elasticity of substitution is constant regardless of the levels of energy use or levels of output.

To identify the price responsiveness of electricity demand between peak and off-peak periods, it can be shown that the ratio on input use is a function of the inverse of the price ratio for the inputs and the parameters of the of δ and σ. This relationship is derived from a model to minimize the electricity cost:

(3) Electricity cost = $P_p\ K_p + P_0\ K_0$,

to produce a given level of the electricity aggregate from equation (1). By manipulating the first-order conditions for this minimization problem, the marginal technical rate of substitution (MTRS), which is the ratios of the marginal products of inputs, is set equal to the price ratio. The marginal products for peak and off-peak electricity are then as follows (see Miller *et al*. (1975) for the most transparent derivation):

(4a) $\partial q / \partial k_p = \delta\ (q / k_p)^{1/\sigma}$ and

(4b) $\partial q / \partial k_0 = (1 - \delta)\ (q / k_0)^{1/\sigma}$.

The ratio of these two equations is the marginal technical rate of substitution (MTRS) of k_0 for k_p:

(5) $\text{MTRS} = [\ \delta /(1 - \delta)\ ]\ (k_0 / k_p)^{1/\sigma}$.

---

[9] The algebra needed to derive this relationship, along with the derivation of the elasticity of substitution, is found in Ferguson (1969, pp. 103-04) and is not repeated here.

The necessary conditions for cost minimization require that MTRS be set equal to the ratio of input prices:

(6) $[\ \delta /(1 - \delta)\ ]\ (k_0 / k_p)^{1/\sigma} = p_p / p_0$

where p_p and p_0 being peak and off-peak prices, respectively. Solving this relationship for the relative intensity of electricity use between peak and off-peak periods, we have:

(7) $k_p / k_0 = \{[\ \delta /(1 - \delta)\ ]\ [p_0 / p_p\ ]\}^{\sigma}$.

The ratio of peak to off peak electricity usage is a function of the inverse price ratios (i.e., the ratio of off-peak to peak prices). The parameters δ (intensity) and $^{\sigma}$ (transformation) characterize the extent to which peak and off-peak usage are substituted as the input price ratio varies.

A Strategy for Estimating the CES Model

If we multiply the right-hand-side of equation (7) by an appropriate error term (ε), and take the logarithms of both sides, we can obtain an unbiased, minimum-variance estimate of σ using ordinary least squares (OLS):

(8) $\ln [\ k_p / k_o\ ]= \sigma \ln [\ \delta /(1 - \delta)\ ] +\sigma \ln [p_0 / p_p\ ] + \ln \varepsilon$.

The parameter σ measures the proportional change in the ratio of electricity use in peak and off-peak periods due to a percentage change in the inverse price ratio. For this production function to be well behaved, Ferguson (1969) shows that $0 < \sigma < \infty$.[10] The higher σ is, the more responsive (in terms of shifting from one period to another) energy use is to changes in relative prices between peak and off-peak periods. For example, if $\sigma < 1$, then as the price ratio changes by one percent, the ratio of peak to off-peak energy use changes by less that one percent. Conversely, for $\sigma > 1$, the ratio of peak to off-peak energy use changes by more than one percent as the inverse price ratio changes by one percent. Analyses of RTP service have produced substitution elasticity values for customer segments that range from 0 to 0.75 (Neenan Associates, 2003; King, 1994).

The estimated constant term from equation (8) is,

(9) $a = \sigma \ln [\ \delta /(1 - \delta)\ ]$.

To recover δ for a given estimate of σ we know that $a / \sigma = \ln [\ \delta /(1 - \delta)\ ]$. Rearranging terms yields the following:

[10] This relationship shows that σ is the proportional change in the use of electricity in the peak period relative to the off-peak period (holding output, in this case the electricity aggregate, constant), as the inverse price ratio increases or decreases by one percent (see Ferguson, 1969, pp. 103-04).

(10.a) $[\ \delta /(1 - \delta)\ ] = e^{a/\sigma}$,

(10.b) $\delta = (1 - \delta)\ e^{a/\sigma}$,

(10.c) $\delta = e^{a/\sigma} - \delta\ e^{a/\sigma}$, and

(10.d) $\delta = (e^{a/\sigma}) / (1 + e^{a/\sigma})$.

We are able to identify all the parameters of the CES function, with the exception of δ, utilizing an Ordinary Least Squares estimator. The intensity parameter (δ) may be critical in simulating firm behavior as part of the process of designing price-responsive load programs.

Empirical Specification of the CES Demand Model

For empirical estimation, it is important to define exactly how the variables used in the regression analysis are calculated from the data. From equation (8), one needs to have the ratio of peak to off-peak electricity use. For each weekday, t, and firm or group of firms, m, define:

k_{ptm} = peak kWh;

k_{0tm} = off-peak kWh;

p_{ptm} = average hourly peak price / kWh; and

p_{0tm} = average hourly off-peak price/kWh.

Many of the firm-level variables collected in the customer survey are included in the initial specification of this model. To illustrate how this is done without including unnecessary algebra, it is sufficient to focus here only on firm-level dummy variables, the weather index and whether or not the firm is a manufacturing company. The firm-level dummies are included only as intercept shifters. However, the weather index and the manufacturing dummy are included as both an intercept and a slope shifter (see Attachment C for discussion of the weather index variable). In the actual estimated model, other variables are included in a similar fashion.

The full model can now be specified as (for all observations across time t):

(11) $\ln (k_{ptm} / k_{0tm}) = a + \sum a_m D_{tm} + b\ w_{tm} + d \ln (p_{0tm} / p_{ptm})$

$+ \{b_m D_{tm} [\ln (p_{0tm} / p_{ptm})]\} + g\ w_{tm} [\ln (p_{0tm} / p_{ptm})] + \ln e_{tm}$

In this most general form, both the distribution parameter, δ, which is embodied in the parameter 'a' of equation (11) differs by firm and weather (w_{tm}).[11] That is for $D_{tm} = 1$ (i.e., a manufacturing firm) we have:

(12) $a_{tm} = a + a_m + b\ w_{tm}$.

If the firm is not a manufacturing company, the term a_m drops out of equation (12). In this specification, there are separate intercepts for each firm and each value of the weather index. These variables affect the relative level of usage between peak and off-peak periods, but not the rate at with usage responds to price.

More important, the price response, σ, also depends on some of these other variables. For $D_{tm} = 1$ (i.e., a manufacturing firm), we have the relevant logarithmic partial derivative given by:

(13) $\partial\ [\ln (k_{ptm} / k_{0tm})\ ] / \partial\ [\ln (p_{0tm} / p_{ptm})\ ] = \sigma_{tm} = d + \{b_m\ D_{tm}\} + g\ w_{tm}$.

This specification implies that price response differs by whether the firm is a manufacturing firm and weather.[12] For the non-manufacturing firm, $\{b_m\ D_{tm}\}$ drops out of the equation. Normally b_m and σ_{tm} would be evaluated at the means of w_{tm}. They could also be evaluated at monthly means etc. During the summer peak months (i.e., June through September), one would expect extremely hot weather to reduce a firm's ability to substitute electricity between peak and off-peak periods. Thus, we would expect g to be negative. Depending on the characteristic being measured by D_{tm} (e.g., whether the firm is in manufacturing), the estimate of parameter a_m and σ_m could be expected to be positive or negative.

One potential disadvantage of the CES specification is that the elasticity of substitution is assumed to be constant (i.e., invariant with respect to initial peak relative to off-peak electricity usage or to the initial relative prices). It is conceivable that some customers are more price-responsive at higher prices. For example, a 10% increase in the peak price from \$0.50 to \$0.55 per kWh might induce a bigger demand response by some customers than would a comparable percentage increase at much lower prices (e.g., \$0.05 to \$0.055 per kWh). This might be the case because a customer incurs fixed costs to curtail, and therefore requires that a certain price threshold be exceeded before they are willing to curtail or because they realize increasing marginal net returns for increased curtailments. This limitation may be addressed by using an Indirect Generalized Leontief Cost Function (see Attachment A).

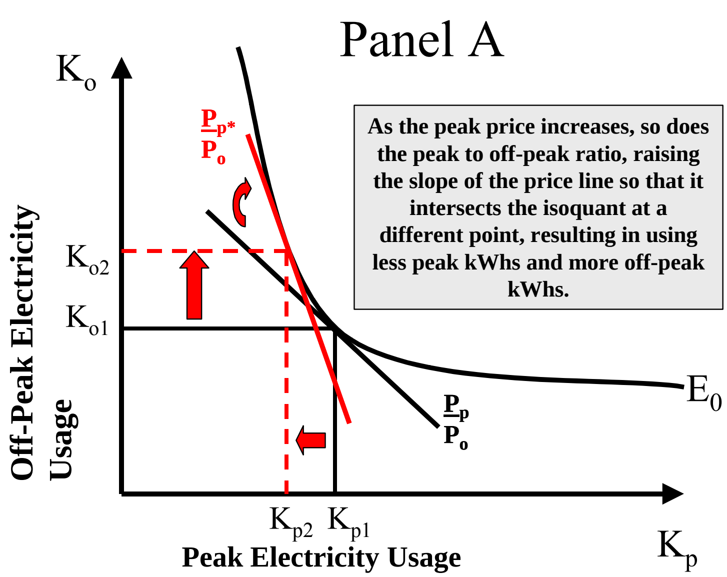
[11] See Attachment C for a definition of the weather index.

[12] This is a model in which the elasticity of substitution is affected by production processes, weather, or other factors specific to the firm, Z_i. It is a simple extension of the CES model, and as Caves and Christensen (1980) demonstrate algebraically that the modification is accommodated in the conceptual model by replacing ρ in equation (1) with $\rho + \sum_i \gamma_i Z_i$.

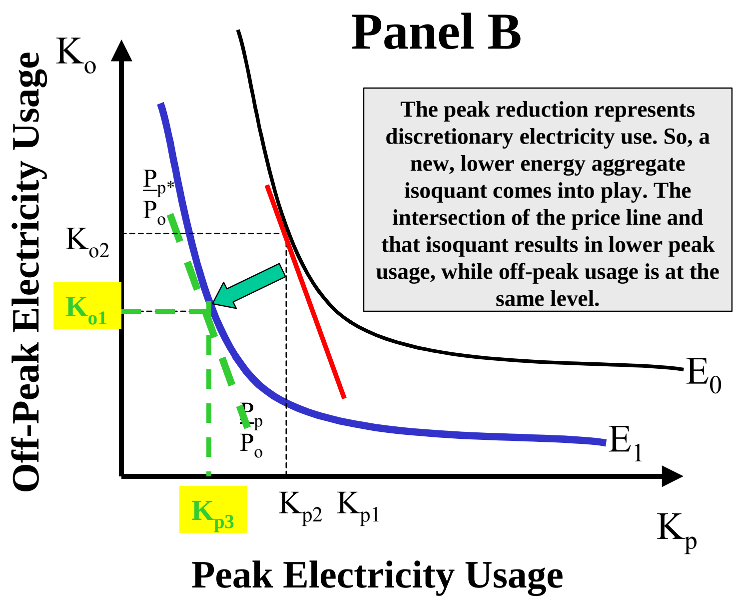
Electricity Conservation vs. Shifting

The CES model assumes that the electricity aggregate of the firm does not change in response to price differences – only the relative peak and off-peak electricity inputs in the production process are altered. Some SC-3A customers indicated in the customer survey that they simply forego using certain electrical equipment or end uses when asked to respond to either system emergency or high prices (e.g., turn off lights).

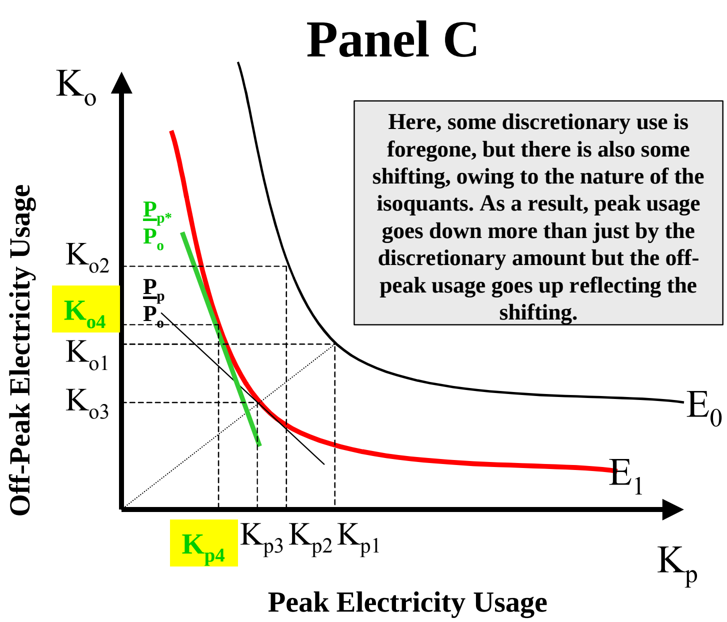
This practice violates the underlying assumption of a CES model that assumes the energy aggregate involves only peak and off-peak energy. The conservation response to price increases suggests that there is another force to be accounted for in the derived factor demand system; customers can forego peak and off-peak usage (e.g., reduced comfort level) for the aggregate electricity input while maintaining firm output. In other words, some customers forego usage altogether, rather than shifting from peak to off-peak periods. In this situation, our estimate of the elasticity of substitution will correctly characterize the shifting effect, but under-estimate the nominal level of the reduction in peak usage.



To see this more clearly, consider Panel A. The curve E_0 represents combinations of the inputs K_{p1} and K_{o1} that produce an energy aggregate that support the firm's desired (and constant) output. At the expected price levels of P_p and P_o, the firm would be expected to use K_{p1} and K_{o1} of peak and off-peak electricity respectively (which is the intersection of the price line in Panel A, with slope Pp/Po, and the isoquant E_0). When the peak period price changes to P_{p*}, the price line's slope increases, and it intersects the isoquant E_0 at a different point, which results in lower peak electricity usage and more off-peak electricity to hold the energy aggregate and output constant. The substitution elasticity measures these input substitutions.



But what if the customer responds to high peak prices by foregoing peak consumption altogether (e.g., a customer elects to reduce occupant comfort by increasing the thermostat setting by 2-4 degrees while still maintaining the firms' output)? As a result, the firm requires less of the energy aggregate to maintain its output level. Since the energy aggregate is lower, a new isoquant now represents the input tradeoff possibilities, which can be illustrated by a shift to the isoquant to E_1 in Panel B. In this simplified case, the shift is such that the off-peak usage stays the same (K_{o1}), while peak usage declines (K_{p3}). In this case, the response is achieved solely by foregoing peak usage. The overall cost of production is still minimized allowing the firm to maintain the same level of output. However, the estimated substitution elasticity, which is based on the energy aggregate remaining constant (i.e., so that substitution is along isoquant E_o), does not reveal the actual nature of the response.



Depending on the shape of the isoquants, which reflect the firm's underlying production processes, it is possible to observe outcomes that involve both load shifting and foregone consumption. In Panel C, the shape of E_0 and E_1 (the isoquants have a different shape) is such that the shift in the price lines result in a different peak (K_{p4}) and off-peak (K_{o4}) level compared to the situation described in panel B. The foregone usage lowers the peak and the off-peak usage, but there is also shifting that further reduces the peak usage and increases the off-peak usage.

To summarize, the surveys administered to NMPC SC-3A customers confirmed that while some customers respond by shifting, others forego discretionary usage, and some do both. Accordingly, while the CES model we specify will correctly characterize shifting behavior in response to price changes, it will underestimate the amount that peak load is reduced by the extent to which customers forego consumption. Fortunately, a means is available for reconciling these behaviors and estimating the final peak reduction amount for a given price change.

Load Response Characterization (LRC) Model: Empirical Specification of Conservation vs. Load Shifting

In addition to measuring the elasticity of substitution between peak and off-peak electricity consumption, it is essential to fully characterize the kind of behaviors that customers engage in to accomplish that change. Specifically, we want to distinguish pure load shifting from responses that involve foregoing consumption.[13] In this section, we describe the Load Response Characterization (LRC) model, which is an empirical approach for adjusting the substitution elasticity to accommodate behaviors other than load shifting. We use the LRC model results as part of our effort to estimate customer's expected reductions in peak usage for a given price change (i.e., demand response).

We employ an analytical framework similar to that used by Patrick (1990) in his analysis of the results of electricity TOU pricing pilot programs, which primarily targeted commercial customers. Patrick postulates that customers can respond by shifting load, foregoing use, and/or conserving, all of which change the peak to off-peak usage ratio, but by different amounts, and which lead to different results in terms of the nominal change in peak usage. In Patrick's formulation, conservation behavior is defined as a special case of foregoing consumption characterized by an equal proportional reduction in peak and off-peak usage within a day.

Load shifting and foregoing consumption comport with reported customer behaviors and response to high prices. For example, in order to shift load, some customers re-arrange their production schedule so that peak electricity usage can be reduced and compensated for by increased off-peak use. Foregone consumption represents short-term sacrifices in terms of the business environment without a commensurate change in the business activity (e.g., reduced amenity level).

[13] In effect customers utilize a slack input that allows the firm's output to continue unabated while lowering electricity consumption, at least for short periods.

However, the conservation case is more difficult to square with rational behavior. Why would a customer that reduces peak usage by foregoing in order to realize bill savings in response to high prices, also reduce their off-peak usage that is subject to much lower prices as part of their short-term behavioral response? Such a response would appear to be at odds with rational economic behavior. But, there are several plausible explanations. The most compelling explanation is that customers encounter indivisibilities, such as having to shut down equipment or processes for a longer period, such as an entire shift, in their efforts to reduce discretionary usage during high-priced peak hours. A second possibility is that this type of customer behavior might reflect a "good citizen" ethic. Customers may reduce their peak usage because high prices are often associated with conditions where system reliability is jeopardized and a public appeal may have been issued to customers urging them to lower consumption (conserve). These customers may then turn off devices for hours that extend well beyond the period of high prices (i.e., the peak period). The consequence of these actions is that the customer's total daily load is reduced proportional to the peak reduction. A third explanation is that conservation may actually reflect the combined effect of a customer taking several actions that involve discretionary curtailments and/or load shifts. These actions cumulatively result in the amount of load shifted such that the change in peak and off-peak usage is proportional (as shown in Panel C).

Following Patrick, to separate shifting affects from those due to foregone consumption, we estimate the following regression equation in the LRC model:

(14) $\{\%\Delta Q_T\} = a + \sum_m (F_m) D_m + \beta_q \{\%\Delta q_p\} + u$,

where:
$\%\Delta Q_T$ = % change in daily kWh usage relative to the daily CBL,
$\%\Delta q_p$ = % change in daily peak period usage relative to the CBL during the peak,
F_m represents firm characteristic variables
D_m are firm dummy variables
a and β_q are parameters to be estimated,
u is an error term, and
CBL is the customer baseline load, which represents the customer's typical usage on days when peak and off-peak prices are relatively low.

This LRC model can be applied to individual customers, to customer aggregates that represent segments or communities of interest, or to the population as a whole. Because the CES model was estimated for customer aggregates (e.g., industrial, commercial, government and education), this relationship is estimated for the same aggregates in the LRC model to support developing a simulation model to forecast nominal peak and off-peak load changes, as described below.

To interpret the coefficients of the LRC model, it is important to remember that as the price of on-peak electricity rises (ceteris paribus), electricity becomes a more expensive input for customers, and there is a tendency for the overall demand for electricity to fall, as customers in effect forego usage based on its cost. However, to hold output constant, customers also have an incentive for some load to be shifted from the peak to the off-peak period. The parameter, β_q, associated with the variable $\%\Delta q_p$ in (14) can be interpreted in a way that isolates these two effects.

The variable $\%\Delta q_p$ measures the combined substitution and conservation effect during the peak period, while its effect, β_q, indicates the proportion of peak conservation behavior that is consistently observed across the entire daily demand cycle. That is, β_q is the proportion of the reduction in peak demand that is due to overall daily energy conservation. Consequently, only that proportion of peak load reduction equal in percentage terms to the percentage downward shift in total daily load due to the higher cost of electricity is counted as conservation. This is as it should be because electricity conserved on a particular day involves foregoing consumption proportionally in both the peak and the off-peak period.[14]

While the coefficient β_q accounts for the proportion of load reduction on peak that is equal to the overall downward shift in daily load, $(1 - \beta_q)$ is the proportion of peak load shifted to off-peak periods. It captures the non-parallel change in the peak to off-peak load shape that is due to the fact that peak price is higher relative to off-peak price, which leads customers to substitute on-peak electricity for off-peak electricity. These measures are exact, provided there is no output effect. By including the D_m variables (e.g., dummy variables representing firm characteristics) as slope shifters, we can test for differences in conservation and load shifting behavior for sub-groups of firms. This allows us to identify characteristics that help us explain which type of behavior is likely to be exhibited.

Given this interpretation of β_q, one would expect that $0 < \beta_q \leq 1$.[15] If β_q were to take on an extreme value of zero, then as peak demand is reduced relative to the customer's CBL in response to higher prices, the entire change would be due to shifting usage from peak to off-peak periods. Conversely, if $\beta_q = 1$, then the identical proportional reduction in peak period usage is also observed in the off-peak period (i.e., a conservation behavioral response or action as defined by Patrick; there is foregone peak load, but none is shifted to the off- peak period). Values between the extremes are somewhat more difficult to interpret. Technically speaking, $\beta_q = 0.5$ implies half of the proportion of load conserved during the peak period is equal to the proportion of load conserved across the entire day. As described previously, several different types of behavior could cause this to happen.[16]

---

[14] We still do not know from this analysis whether the electricity conserved on the day is never consumed or is consumed on another day. Such an analysis is beyond the scope of this research.

[15] Values outside this range simply reflect unusual load profiles, i.e. extreme cases.

[16] First, if the peak load and off-peak load are identical but the load reduction is only observed in the peak-period, then 50% of the peak load reduction is counted as a daily reduction in load. To illustrate, let x equal the reduction in demand on peak. If Y is the identical in level of peak and off-peak load, then (x/Y) represents the proportional reduction in peak demand, while $(x/2Y) = (1/2) * (x/Y)$ represents the proportion of daily load reduction. Only half of the peak load reduction is considered conserved since the curtailment was not consistently maintained throughout the day. Alternatively, it could be that off-peak load is three times that of on-peak load. If the reduction in load on-peak is x but off-peak load is also reduced by x, then the proportion of load reduced on peak remains $(x\backslash Y)$ while the proportion of load

Table E-1 shows four examples that illustrate the LRC model's assumptions, along with the interpretation of these results. In these four examples, assume that a group of customers reduce their peak usage by 20 MWh (or 50%) relative to their expected peak usage under "baseline" conditions. In Case 1, these customers increase their off-peak load by 20 MWh, which exactly offsets their peak load reduction and results in no net change in load across the day. Such a consumption pattern is characterized as complete substitution or load shifting (Beta = 0). Case 2 represents the opposite extreme in which customers reduce peak and off-peak load within the day by 50%, which causes the daily load to be half the daily CBL. Since the proportional load reduction is identical in both time periods, the model identifies this behavior as conservation (Beta = 1.0).

Table E-1. Shifting vs. Conservation Model Example

Cases	Peak Load	Peak CBL	Peak Load	Peak CBL	Daily Load	Daily CBL	%Diff-Peak	Off Peak	%Diff Daily	Implied Beta	Amt. Cons.	Amt. Shifted
1	20	40	70	50	90	90	-0.50	0.40	0.00	0.00	0.0	20.0
2	20	40	25	50	45	90	-0.50	-0.50	-0.50	1.00	20.0	0.0
3	20	40	50	50	70	90	-0.50	0.00	-0.22	0.44	8.9	11.1
4	20	40	40	50	60	90	-0.50	-0.20	-0.33	0.67	13.3	6.7

Case 3 assumes that customers reduce their expected peak load by 50% but do not alter behavior in the off-peak period. These types of discretionary load curtailments result in a mitigating effect on the daily load reduction (50% for the peak period vs. 22% for the entire day). That portion of peak CBL that is equal to the proportional reduction in load across the entire day is counted as conservation (e.g. 22% * 40 MWh = 8.9 MWh). Thus, of the total 20 MWh peak load reduction, about 8.9 MWh is identified as conservation because the proportional reduction in the peak period is not consistently and universally maintained across the day. The remaining 11.1 MWh is considered shifted from peak to off-peak periods. In the fourth case, customers reduce load in both the peak and off-peak periods but in different proportions (compared to case 2). Once again, the effect is that the daily deviation from the CBL is lower than in the peak period because off-peak curtailments were lower as a proportion of CBL. In case 4, about 13.3 MWh of the 20 MWh peak load curtailment is considered conservation while the remainder is identified as load shifting.

Estimating Aggregate Demand Response

The CES and LRC models can be utilized to simulate the amount of load curtailed at different prices by customers during the peak period. In effect, it is possible to construct a supply curve of customer demand response based on the estimated elasticity values. These estimates of demand response are of interest to policymakers, utilities and ISOs. For example, it would be helpful for NMPC to forecast the expected level of load

reduced in the day is $[(x + x) / (Y + 3Y)] = (2x/4Y) = (x/2Y) = (1/2) * (x/Y)$. Once again β_q is estimated to be 0.5 but for an entirely different type of behavior.

reduction from SC-3A customers if prices are high as the utility decides how to adjust load purchases in the NYISO Day-Ahead Market. This information may also help the NYISO, who must secure the bulk power system against possible contingencies. Regulators interested in promoting demand-side price-responsiveness could also benefit by using the estimates to set reasonable goals for RTP (or DR) programs.

By definition, the elasticity of substitution is a percentage change in the peak to off-peak ratio of demand for a 1% change in the off-peak to peak price ratio. In order to assess what happens to the ratio of peak to off-peak load as prices change, the elasticity estimate can be rearranged to produce the expected ratio of peak to off-peak electricity as follows:

(15) $\sigma = \{ [(k_p/k_o) - (k^*_p/k^*_o)] / (k^*_p/k^*_o) \} / \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$

(16 $\{ [(k_p/k_o) - (k^*_p/k^*_o)] / (k^*_p/k^*_o) \} = \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$

(17) $[(k_p/k_o) - (k^*_p/k^*_o)] \} = \sigma (k^*_p/k^*_o) \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \}$

(18) $(k_p/k_o) = (k^*_p/k^*_o) \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)$,

where k_p and k_o represent actual peak and off-peak electricity consumption at the observed peak and off-peak price of p_p and p_o respectively, and k^*_p and k^*_o represent a reference CBL peak and off-peak electricity consumption at a reference peak and off-peak price of p^*_p and p^*_o respectively.

In order to estimate the actual on-peak and off-peak load expected to be induced by customers' price response, we must make an assumption regarding the nature of the observed changes in electricity consumption. Specifically, we assume that total load in the day remains constant regardless of price changes.[17] If total load is unchanged, then k_o (off-peak load) can be re-specified using k_p, k^*_p , and k^*_o as follows to get a single expression for actual on-peak electricity consumption (k_p):

(19) $[k_p/ (k^*_p + k^*_o - k_p)] = (k^*_p/k^*_o) \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)$

(20) $k_p = (k^*_p + k^*_o - k_p) \{ (k^*_p/k^*_o) \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\}$

(21) $k_p = (k^*_p + k^*_o) \{(k^*_p/k^*_o) \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} / [\{ (k^*_p/k^*_o) \sigma \{ [(p_o /p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} + 1]$

To estimate k_p, the peak load that would result from a price change from p^*_o and p^*_p to p_o and p_p, requires specifying the reference peak and off-peak loads under "normal" conditions and prices (which we define as the average prices during the periods used to calculate the CBL). We use the definition of CBL in the LRC model, along with the substitution elasticities estimated in the final CES model in order to predict the amount of

[17] This assumption would be generally consistent with the CES models' assumption of a constant energy aggregate, but would not require one to solve for the energy aggregate itself.

peak load that would be curtailed in response to a change in the ratio of off-peak to peak prices. Because the CBL was estimated for days less than $0.075/kWh, the demonstration simulation exercise begins with this price and increases it by $0.025/kWh increments until the market cap of $1.00/kWh is reached.[18] At each price point, the level of peak demand is calculated and the difference between this estimate and the CBL represents the amount of demand response that would be forthcoming at that price.

In terms of our specific application, we constructed the aggregate demand response supply curve by utilizing the elasticity estimates from the "final" CES model results for 32 customers and applying these elasticity estimates to the 141 customers in the SC-3A target population. However, in the "final" CES model, we include several categorical variables (drawn from the customer survey) that are not known for the entire SC-3A target population. Thus, in order to extrapolate the elasticity results from the 32 customers to the 141 customers in the SC-3A target population, we grouped the "final" elasticity results in a manner that is consistent with the groupings available for the target population of customers.[19] Thus, we assigned each customer in the target population to one of these categories and then designated the elasticity estimate from the final CES model results for that category in an attempt to characterize their expected price responsiveness.

One drawback of this simulation model is the effect of the constant daily load assumption on the estimated peak load reduction. As previously noted, several customers indicated they undertake simple curtailment measures that do not require the firm to increase use in another period. This would cause daily load to decrease while potentially causing off-peak load to instead remain constant. By requiring daily load to be fixed, the CES model elasticity estimates under-estimate the customer's peak-load reduction since it does not account for the lower overall daily load that would have occurred. If instead off-peak load is held constant in the simulation model, the load curtailment on-peak for customers who execute these simple behaviors is correctly predicted, but will bias upwards those customers who perfectly shift their consumption from peak to off-peak periods. Another adjustment method must be found to consistently predict as accurately as possible the peak load reductions of customers who exhibit these different types of behavior.

Adjusting Aggregate Load Response for the Conservation Behavior Effect

As demonstrated above, to predict the nominal kWh reduction in peak and off-peak given a specified change in the ratio of peak to off-peak prices, it is necessary to adjust the substitution elasticity to account for the conservation behavior effect. Estimating the LRC model, adapted from Patrick (1990), provides an estimate of the conservation effect from daily deviations from CBL as a proportion of peak period deviations.

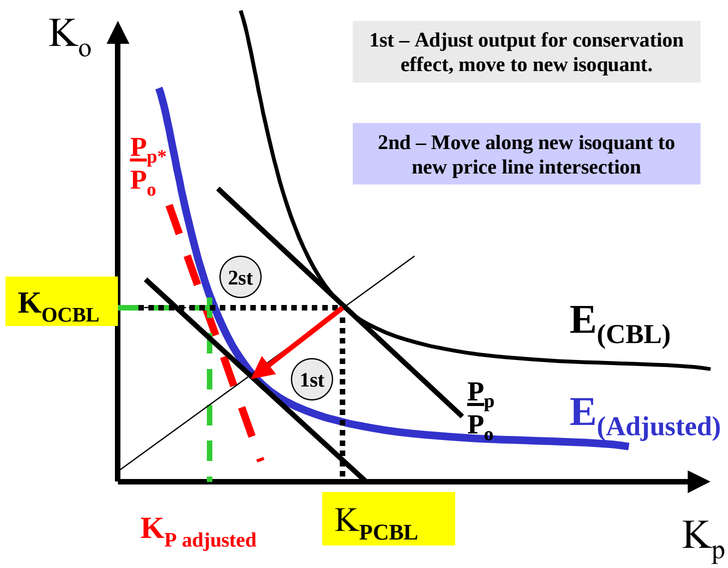
---

[18] In some cases, the average price during the peak period on "CBL" days could be less than $0.075/kWh, in which case there would be an expected curtailment, however small, at even this low price.

[19] We summarized elasticity estimates for the 32 customers included in the "final" model results segmented by market segment (e.g., industrial, commercial, government/education) and participation status in NYISO DR programs, because this information was also available for each customer in the target population.

Panel D illustrates the process. First, the estimate of the conservation effect, β_q, is used to adjust the firm's typical (CBL) load downward to a new isoquant. Then, the substitution elasticity is applied to the adjusted CBL to derive estimates for the new peak and off-peak kWh levels consistent with the new price ratio. The difference between the original CBL and the new estimated load is the total adjustment due to the price change.

Panel D



Peak Electricity Usage

To operationally apply this methodology requires knowing how to adjust the CBL for the expected conservation effect. We define the CBL as the level of usage that the customer would have used absent the price change. To make this adjustment, it is necessary to know either the expected level of conservation in the peak period or the expected level of conservation across the day. Since neither is known definitively, the originally simulated value for peak load (k_p), as estimated using (21),

$$(21)\ k_p = (k^*_p + k^*_o)\ \{(k^*_p/k^*_o)\ \sigma\ \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} / [\ \{ (k^*_p/k^*_o)\ \sigma\ \{ [(p_o/p_p) - (p^*_o/p^*_p)] / (p^*_o/p^*_p) \} + (k^*_p/k^*_o)\} + 1\ ]$$

and the estimated conservation coefficient (β), from (14) above, can be used to calculate an estimate of the percentage change in total load as follows:

$$(22)\ (k^{**}_T - k^*_T)/(k^*_T) = \alpha + \beta\ [(k_p - k^*_p)/(k^*_p)]$$

If the intercept term, α, is assumed to be zero, then 100% of daily deviations from CBL are attributable to "conservation" behavior, even though there may be peak and off-peak changes that result from combinations of shifting and conservation efforts. So if the overall daily load is reduced, the peak and off-peak load must also be adjusted downwards by this same proportional amount to account for the effects of conservation.

This is accomplished by calculating an "adjusted" peak and off-peak CBL (k^{**}_p and k^{**}_o respectively) as follows:

$$(23)\ k^{**}_p = k^*_p\ [(k^{**}_T - k^*_T)/(k^*_T)\ ]$$

$$(24)\ k^{**}_o = k^*_o\ [(k^{**}_T - k^*_T)/(k^*_T)\ ]$$

These "adjusted" CBL values are assumed to represent a point on a lower isoquant, since the total energy aggregate has been reduced while total firm output has been maintained. The difference between the original CBL and the "adjusted" CBL represents the amount of load conserved. The original CBL values in (21) are replaced with the "adjusted" CBL values from equations (23) and (24) to simulate what the "corrected" estimate of peak and off-peak load for the given change in prices and estimated elasticity of substitution:

$$(25)\ k^N_p = (k^{**}_p + k^{**}_o)\ \{(k^{**}_p/k^{**}_o)\ \sigma\ \{\ [\ (p_o/p_p) - (p^*_o/p^*_p)\ ]\ /\ (p^*_o/p^*_p)\ \} + (k^{**}_p/k^{**}_o)\}\ /\ [\ \{\ (k^{**}_p/k^{**}_o)\ \sigma\ \{\ [\ (p_o/p_p) - (p^*_o/p^*_p)\ ]\ /\ (p^*_o/p^*_p)\ \} + (k^{**}_p/k^{**}_o)\} + 1\ ]$$

$$(26)\ k^N_o = k^{**}_T - k^N_p$$

Together, an estimate of the substitution elasticity and an estimate of the conservation effect provide the means for estimating the changes in energy use on both peak and off-peak periods. They also provide the basis for simulating the impact of price changes on peak consumption (which is the focus of most demand response programs) and off-peak consumption, a collateral impact that is important for fully characterizing the program impacts.[20]

Final CES Model Results

In the *Final* CES model, we tested a number of variables derived from customer survey responses. Our goal was to see if additional, in-depth information about customer circumstances would provide for a more robust characterization of electricity usage, and identify important drivers to price response.

Model Specification

Many of the survey-derived variables proved to be insignificant in explaining differences in groups and were omitted.[21] However, several variables provided important explanatory information and were included:

---

[20] The revenue impact of demand response has been an issue in program design. For example, the PJM real-time pricing program deducts from the participant's curtailment payment an amount that represents the T&D revenue the wires company would have received, but for the curtailment. However, there is no attempt to ascertain if the customer's response was discretionary curtailment or load shifting. If the response is the latter, this transfer amounts to a windfall rents to LSE.

[21] In some cases the variables provided redundant measures to factors already included. In others, the hypothesized effect was not forthcoming in terms of a parameter estimate that was statistically significant.

- *Time of Peak Usage*: The information that customers provided about when their load peaked was used to design an alternative indicator of the ability to shift; whether peak usage occurred between noon and 5 pm, or some other time of the day.
- *Relative importance of electricity costs*: Survey respondents' assessment of their electricity costs as a percent of annual operating costs was also assigned to a variable. Customers were sorted according to whether they reported their electricity costs were equal to or greater than 10% or less than 10% of operating costs.
- *Investments in DR enabling technologies*: We posited that customers that had invested in various DR enabling technologies that helps them shift load would be more price responsive. A dummy variable was constructed to reflect whether the customer had made a technology investment after the start of the RTP-based SC-3A service in 1998 and another dummy variable for similar investments prior to 1998.[22]
- *Participation in NYISO EDRP*: To isolate the impact of these additional inducements to curtail from NYISO programs, the dummy specification also distinguished between EDRP event days, and other "non-event" days, thereby allowing for the elasticity of EDRP participants to vary according to whether the customer faced SC-3A prices or was provided an additional inducement ($.50/kWh) to curtail. Our hypothesis was that the extra inducement would increase price response, over what the customer would otherwise accomplish based on SC-3A prices.

Hourly price and load from 32 customers were used to estimate the Final CES models.[23] This reduction in sample size resulted from the pattern of survey responses; only those customers that answered *all* the relevant questions could be analyzed.[24]

Model Parameter Estimates

Table E-2 summarizes the model estimates. The high F-Test values support rejecting the hypothesis that all the parameters values are in fact zero, and indication of the robustness of the specification. Overall the model explained about 25% (R^2) of the variation in customer's peak usage ratio over the three summer periods. Because there are only about 25% as many customers in this model as were used in the initial specification, a lower R^2 is to be expected.

[22] In creating the dummy variable for investments in DR enabling technologies, customers that invested in process/building automation systems, control devices on specific equipment or processes, or peak load management control devices were coded as "1"; other responses were coded as "0" (see question 31 in survey)

[23] We used dummy variable slope shifters to distinguish differences in elasticity among the three business sectors (Government/education, Industrial, Commercial) thereby allowing for an individual substitution elasticity estimate for each sector and to reflect enrollment in NYISO DR programs.

[24] In order to include answers to a survey question in the estimated demand equations, survey respondents had to provide a definitive answer: either a "Yes" or a "No". A choice to not respond to the question, which was an option on every question, provides no information concerning classification of the explanatory variable and thus, that customer was omitted from the final CES model sample.

Table E-2. Final CES Demand Model Parameter Estimates

Variable	Short Peak		Medium Peak		Long Peak	
Log Inverse Price Ratio	0.03		-0.02		-0.02	
Slope Shifter Variables - the parameters values are add to the intercept to derive the corresponding substitution elasticity estimate						
Business Sector						
Gov't / Education	0.63	*	0.58	*	0.52	*
Commercial	0.34	*	0.30	*	0.28	*
Industrial	0.30	*	0.29	*	0.26	**
Other Factors						
Peak Usage Noon-5 PM	-0.23	*	-0.21	*	-0.19	*
Electricity Cost > 10% Op Cost	-0.10	**	-0.08	**	-0.08	**
Investment made prior to RTP	-0.18	*	-0.13	*	-0.11	**
Investment made while on RTP	-0.07		-0.05		-0.04	
Temp > 70	0.01		0.02		0.02	
Year=2001	0.00		-0.01		0.00	
EDRP Non-Event Days						
Gov't/Ed EDRP Participant	-0.05		-0.08	**	-0.10	*
Commercial EDRP Participant	-0.13	***	-0.10		-0.08	
Industrial EDRP Participant	-0.30	*	-0.25	*	-0.21	*
Other EDRP Participant	-0.16	***	-0.17	**	-0.19	**
EDRP Event Days						
Gov't/Ed EDRP Participant	-0.07		-0.09		-0.07	
Commercial EDRP Participant	-0.16		-0.13		-0.12	
Industrial EDRP Participant	0.47	*	0.38	*	0.37	*
Other EDRP Participant	0.43	*	0.44	*	0.43	*
Other NYISO PRL Participation						
NYISO DADRP Participant	0.52	*	0.43	*	0.33	*
NYISO SCR Participant	0.18	**	0.18	**	0.16	**
R-Squared	0.23		0.25		0.27	
F-Test of Global Significance	34.04	*	37.20*		41.72	*

Short Peak = 2:00-5:00, Medium Peak = 1:00-5:00, Long Peak = Noon - 5:00
* = Significant at 1% level
** = Significant at 5% level
*** = Significant at 10% level
Values less than 0.005 appear as 0.00 due to rounding
32 Customers included

The estimated parameters for the Final CES model are presented for the three alternative peak specifications, Short (2-5:00 p.m.), Medium (1-5:00 p.m.), and Long (noon-5:00 p.m.) of what constitutes the daily peak period. In general, the parameter estimates get smaller as the peak period definition gets longer. This is to be expected. A longer peak means that shifting to avoid the prices in that period requires a greater effort. The Long peak is comprised of the entire afternoon, so shifting load to off peak in effect requires rearranging the entire day's activities. The Short peak, in contrast, leaves more room to maneuver, since the early afternoon hours are available (off-peak) to make up for the peak load reduction. In our discussion, we will refer primarily to parameter estimates for the Long peak period (noon – 5 pm), as it had the best fit results for the CES model.

Importantly, three of the variables derived from the survey data are significant and have a substantial impact of the elasticity estimates. These results indicate that participation in other NYISO DR programs (DADRP and ICAP/SCR) enhances price response (the base elasticities are increased by 0.33 and 0.16 respectively). This is not surprising, since both programs provide additional financial incentives to curtail and assess penalties for non-compliance.[25]

Customers that report peak usage between noon and 5:00 p.m. and those with high electricity intensity are less responsive than other customers, all else equal. Specifically, customers that peak during mid-day or indicate electricity costs exceed 10% of total costs would reduce their substitution elasticity by 0.19 and 0.08 respectively. This is consistent with the notion that it is harder for customers to curtail when critical business activity and electric use coincide with times of high prices.[26] However, note that subtracting these amounts from the base elasticities above for the three business sectors still leaves positive elasticity values.

However, the technology investment results are counter-intuitive. The negative marginal elasticities indicate that investing in enabling DR technologies actually decreases price responsiveness. This effect is much more pronounced for the DR investments made before 1998. For investments made after 1998, the negative impact on elasticity is small, but we would expect these DR-oriented investments to facilitate price response. It may be that customers have received peak load management devices or information systems from NMPC or through NYSERDA public benefit programs, but have not taken full advantage of their capabilities. Many customers reported that they made EIS investments in an attempt to better understand the overall load profile at their facility, not to expressly improve their ability to be price-responsive. Information from EIS and EMCS were often used to reduce overall electricity consumption as well as reduce usage during peak periods.[27] Another possibility is that the equipment was installed relatively recently so

[25] ICAP/SCR allows customers to sell their curtailment capability to a load-serving entity to meet its installed capacity requirement. Customers receive an energy payment for their load reduction if called. Failure to comply with curtailment events can result in financial penalties and a derating of the curtailable load the customer can sell in the future.

[26] However, other studies of industrial response to RTP have found the opposite result: that customers with more electricity-intensive production tend to be more, not less, responsive (Christensen Associates, 2000).

[27] In addition, the decision to invest in enabling DR technologies is assumed to be exogenous (i.e., independent) of price-responsiveness in our model specification. Many believe that customers invest in technology because they already are savvy about their electricity demands. To mitigate the possible effects of this assumption, a choice model could be developed to predict investment in energy management equipment, the results of which would be included in the model as a truly exogenous explanatory variable. Time and resources did not permit such activities in this phase of the analysis, but is a subject for continuing research in this area.

that it was not available during the period covered by our demand modeling.[28] Finally, investments in DR-enabling technologies may be correlated with other factors that reduce price response but are not accounted for in the model. Further research is needed to more clearly specify the impact of technology on price response. The last two factors, temperatures over 70 degrees and the year 2001 (characterized by much higher price volatility) have negligible incremental impacts on the elasticity.[29]

The substitution elasticities derived from the Final CES model for the Long peak period are presented in **Table E-3**. The average load-weighted substitution elasticity over all business categories, customer circumstances, and other influences was 0.14, which is double that derived from the Initial CES model.

Table E-3. Final Model Elasticity Estimates for Long Peak

		Gov't/Ed	Commercial	Industrial	Other
1	Just SC-3A*	0.50	0.26	0.24	-0.02
2	SC-3A/EDRP/ Non Event Days*	0.40	0.18	0.03	-0.21
3	SC-3A/EDRP/ Event Days	0.34	0.06	0.40	0.22
	Additional Factors (add to cell values above)				
4	DADRP Participation		0.33		
5	ICAP/SCR Participation		0.16		
6	Peak Usage 12 Noon - 5 PM		-0.19		
7	Electricity Costs over 10%		-0.08		
8	Investment Prior to 1998		-0.11		
9	Investment After 1998		-0.04		
10	Temp > 70		0.02		
11	Year = 2001		0.00		

Moreover, the Final model specification reveals greater variation among the average elasticity values for the three customer groups, to wit: Government/education (0.30), Industrial (0.11), and Commercial (0.0). The industrial value is in the range of what studies of other RTP programs have produced (Schwarz et. al., 2002, Herriges et. al. 1993). The estimated elasticity for the Government/education group is surprising, as it exceeds that of industrial customers that are generally considered to be the best equipped to respond to prices.[30]

[28] NYSERDA implemented programs beginning in 2001 that provided incentives to customers to install technologies that would assist them in responding to the NYISO demand response programs. However, many projects were not operational until the summer of 2002 so the cumulative impact is not reflected in the modeled data.
[29] Because hot days are often associated with high day-ahead prices and EDRP and ICAP/SCR events, isolating a separate heat effect is difficult.

[30] Schwarz et. al. (2002) also found relatively high elasticity for a comparable group.

The unbundled estimated substitution elasticity results are presented by business sector (the columns in Table E-2) in a progressive order, beginning with the elasticities for Just SC-3A customers (Row 1), representing customers on SC-3A tariff but not enrolled in a NYISO DR program. The Just SC-3A elasticity value for the Government/education (0.50) sector is over twice that of the Commercial (0.26) and Industrial (0.24) sectors.[31]

Under most circumstances, government/educational customers are significantly more price responsive than other customer groups. This is in stark contrast to the findings of previous RTP studies in which price response of industrial customers (as measured by elasticity values) is typically much higher than other customers. However, on EDRP event days, government/education EDRP participants are ~30% less price elastic than non-participant government/education customers. This may indicate that these customers have already curtailed or shifted load in response to SC-3A day-ahead prices when the NYISO calls an EDRP event, leaving limited opportunities to shed additional load, even at the higher EDRP inducement price. This explanation is based on the notion that some customers have a maximum amount of curtailable load.[32]

Industrial customers enrolled in EDRP, on the other hand, show dramatically higher price response during EDRP events compared to industrial customer response to SC-3A prices alone: 0.40 substitution elasticity during EDRP events vs. 0.24 for customers not enrolled in EDRP and 0.03 for non-event days for industrial customers enrolled in EDRP. For these customers, the EDRP program appears to entice price response that SC-3A prices do not.

Rows 4 and 5 indicate that participation in other NYISO DR programs further enhances price response. The incremental elasticity values are 0.33 and 0.16 for DADRP and ICAP/SCR, respectively (for each business sector, these values are additive to those from rows 1-3, if the customer is a program participant). The ICAP/SCR result is expected, as these customers face potentially significant penalties for failure to comply with the curtailment order, and in addition they receive an energy payment for their load reduction.[33] The DADRP estimate suggests the prospect of getting paid to curtail boosts customer response over that which would be forthcoming from SC-3A prices alone.[34]

---

[31] Customers in the Other category represent an aggregation comprised of several customers of unique identity and circumstances that require masking. Moreover, their elasticity estimates are generally insignificant and have the wrong sign.

[32] Typically, EDRP events are preceded by high day-ahead market prices, which are the basis for SC-3A prices. The model we employed assumes that elasticity is constant at all prices; thus computed elasticities may be lower if prices continue to increase after customers have reached their maximum load-shedding capability than they would be for the same load response at lower prices. Further research using demand models that do not impose this constant-elasticity constraint, augmented by customer interviews on their curtailment potential, may help resolve this apparent paradox.

[33] ICAP/SCR allows customers to sell their curtailment capability to a load-serving entity to meet its installed capacity requirement. Failure to comply with curtailment events can result in financial penalties and a derating of the curtailable load the customer can sell in the future.

[34] DADRP allows customer to bid curtailments into the NYISO day-ahead market, and if scheduled, receive the day-ahead market price if they curtail as scheduled the next day. In effect, they get paid to respond to prices that are themselves an inducement to respond, which some argue is a double payment.

Rows 6-11 in Table E provide elasticity estimates associated with other influences. Elasticities are decremented for customers (of all sectors) that report having their peak usage between noon and 5:00 p.m. (by 0.19), electricity costs that exceed 10% of total costs (by 0.18), and invested in enabling technology before and after 1998 (by 0.11 and 0.04 respectively). The first two results seem sensible: all other things equal, it is harder for customers to curtail when business activity and electric use coincide with times of high prices. The technology investment (a decrement to the elasticity) results seems counterintuitive, and may represent a correlation with such reported investment behavior and some other deleterious factor to price response. This is another anomalous result that merits further research to resolve. The last two factors, temperatures over 70 degrees and the year 2001 (characterized by much higher price volatility) have negligible incremental impacts on the elasticity.[35]

In summary, the estimated average business class elasticities belie the diversity of response among customers in the same business classifications. Participation in NYISO EDRP program has a profound correspondence with customer response; in some cases associated with an augmentation of the price response induced by SC-3A rates (e.g., Industrial customers). In addition, there is strong complementarity between the ICAP/SCR program and SC-3A. These findings lend support to proponents of ISO DR programs in conjunction with RTP-type rate designs, even if RTP participation is the utility standard offer tariff.

Attachment A: The Generalized Leontief Specification

The CES model is commonly used to estimate the demand for electricity because it provides a consistent representation of cost-minimizing behavior and lends itself to straightforward statistical estimation. However, its implicit assumption about the nature of substitution, that it is constant regardless of relative prices, is restrictive, particularly in light of our customer survey and demand modeling results.[36]

An alternative specification of electricity demand is based on the Indirect Generalized Leontief (GL) Cost Function. We discuss the GL model specification in this attachment as it constitutes a logical next step in evaluating SC-3A customer response. To begin, as before, we specify a firm's production function that is separable in electricity inputs as:

(1a) $Q = F(x_1, x_2, \ldots, x_n, q(k_1, \ldots, k_n))$,

However, these results suggest that customers treat the two situations differently when it comes to adjusting usage.

[35] Because hot days are often associated with high day-ahead prices and EDRP and ICAP/SRC events, isolating a separate heat effect is difficult.

[36] We found that some customers that participate in the NYISO EDRP program, which offers a floor price of $0.50/kWh for curtailments, are much more price-elastic than other customers that are not exposed to these high prices in their SC-3A rates.

where Q is output, x_i are inputs other than electricity, and $k_i, \ldots, k_n$ are amounts of electricity used during periods i through n, respectively. Because production is assumed to be separable in electricity inputs, we can specify the function F as above, where the electricity inputs can be combined according to an aggregator function q. This is essentially being able to specify a sub-function within F. Any combination of $k_1, \ldots, k_n$ that yields the same value for q is equally productive in producing Q. It is the nature of this sub-function that determines the substitutability of electricity among different periods of the day.

Appealing to duality theory (Shephard, 1970), we can also, in theory, specify the indirect cost functions associated with both the production function Q and the sub-function q above.[37] Because of the assumption that the function is separable in electricity inputs, we are only concerned with the indirect cost function associated with the electricity aggregate's sub-function. From that sub-function, we can derive expressions for the elasticity of substitution among electricity use during different times of the day.

If we assume that the underlying aggregator function for q is linear homogenous in the electricity inputs (k_i) and that the indirect cost function C is a flexible generalized Leontief function, then we have for n daily time periods (for i, j = 1,…,n):[38]

(2a) $C = q \{\sum_i \sum_j d_{ij} (p_i\, p_j)^{½}\}$;

This function is linear homogenous in all prices, which is a requirement for a well behaved indirect cost function. That is, if all prices are changed in the same proportion, then C changes in the same proportion as well. We also require that $d_{ij} = d_{ji}$, for symmetry.

From Shepherd (1970), we know that optimal factor demands can be determined by differentiating (2) with respect to each price (i = 1, … ,n):

(3a) $\partial C/\partial p_i = k_i = q\, [\sum_j d_{ij} (p_j / p_i)^{½}]$.

One purpose of flexible cost functions is to facilitate the estimation of the Allen (1938) partial elasticities of input substitution, which, for a cost function (21), are equal to:[39]

[37] This involves solving the first-order conditions to the constrained optimization problem for minimizing the cost of producing a given output for the factor demands and substituting them back into the direct cost function. This procedure allows one to write the indirect cost-minimizing cost function in terms of output and input prices only.

[38] Diewert (1974) shows that if the generalized Leontief function (or any cost function) can be decomposed in this form, then the underlying aggregator function for q reflects a constant returns to scale technology.

[39] As discussed originally by Allen (1938, pp. 508-09), the partial elasticity measures the degree to which the demand for factor j changes as the price of factor i changes. If $\sigma_{ij} > 0$, and the price of factor i increases, then the use of factor j increases, thereby taking part in the replacement of factor i in production. The two factors are said to be *competitive*. If, on the other hand, $\sigma_{ij} < 0$, the two factors are *complements*, and as the price of one of them rises, the demand for both falls. Competitiveness between factors is, on the whole, more general than complementarity. One factor cannot be complementary with all others. In the two input case, direct elasticity of substitution (which measures the percentage change in factor intensities as the inverse price ratio changes by one percent) is equal to the Allen partial elasticity of substitution.

(4a) $\sigma_{ij} = C_{ij} / [C_i C_j]$,

where the subscripts refer to the first and second order partial derivatives of C with respect to inputs i and j. Evaluating equation (4a) for the GL cost function given in equation (3a), we have:

(5a) $\sigma_{ij} = ½ [C d_{ij} (p_i p_j)^{-1/2}] / [q a_i a_j]$,

for all i and j, but $i \neq j$ and $a_i = k_i / q$. In contrast to the CES model, the elasticity of substitution for the GL model varies from observation to observation. In this case, the Allen partial elasticity of substitution varies with price ratios, the energy aggregate and the cost minimizing input levels. Further, for the Allen own partial elasticities of substitution, we have (for all i):

(6a) $\sigma_{ii} = -½ [C \sum_{j \neq i} d_{ij} (p_j^{-1/2} p_i^{-3/2})] / [q a_i^2]$.

Normally, to estimate the parameters of this cost function, one need only assume an additive error structure associated with the input demand equations (3a), and then estimate them as a system of equations where there are across-equation restrictions to insure symmetry of the parameters. This is accomplished most conveniently by dividing each equation by q (Berndt, 1991). That is, one can simply estimate for all i:

(7a) $a_i = k_i / q = [\sum_j d_{ij} (p_j / p_i)^{½}]$.

When j = i, we have $(p_j / p_i) = 1$, and d_{ii} is a constant in the equation for a_i. In this formulation, one can implicitly restrict the coefficients to be symmetric by always writing the subscripts in the same order.

Unfortunately, because q in this case is the energy aggregate and cannot be observed directly, it is impossible to employ this strategy. However, using full information maximum likelihood (FIML) methods within PROC MODEL in SAS, one can estimate the parameters from equations for the ratios of the a_i. That is, we can estimate (for all $i \neq m$):

(8a) $k_i / k_m = [\sum_j d_{ij} (p_j / p_i)^{½}] / [\sum_j d_{mj} (p_j / p_m)^{½}]$.

Within PROC MODEL one can also impose the symmetry restrictions on d_{ij}, and force the adding up restrictions to ensure the function is well behaved globally, $\sum_i \sum_j d_{ij} = 1$.

In this form, the equations are extremely non-linear in the parameters, and it might be best to take the logarithms of both sides for estimation purposes:

(8a') $\ln [k_i / k_m] = \ln \{[\sum_j d_{ij} (p_j / p_i)^{½}] / [\sum_j d_{mj} (p_j / p_m)^{½}]\}$.

This strategy will not eliminate the non-linearity, but it will convert each equation into the differences between two logarithms within which there are coefficients imbedded. Whether SAS deals with that kind of non-linearity better than these quotients is an empirical question.

To evaluate the elasticities of substitution at every data point using equations (5a) and (6a), one needs estimated (or predicted) values of a_i, and C/q, the cost per unit of the electricity aggregate. One can predict a_i directly by substituting the estimated parameters into equation (7a). For convenience label these $(a_i)_{fit}$. Following Berndt (1991), one can obtain predicted values for C/q in the following way:

(9a) $(C/q)_{fit} = \sum_i P_i \, (a_i)_{fit}$.

These predicted values for each data point are then substituted into equations (5a) and (6a) to obtain elasticities of substitution.

To estimate the GL model above, one must also define exactly how the variables used in the empirical regression analysis are calculated from the data. From equation (8a'), we need to have the ratio of peak to off-peak electricity use.

Define for each weekday, t, and firm or group of firms, m:

k_{ptm} = peak kWh;
k_{0tm} = off-peak kWh;
p_{ptm} = average hourly peak price / kWh; and
p_{0tm} = average hourly off-peak price/kWh.

There are also several other variables that must be included in the model; they must be defined specifically. One set contains 0-1 or 'dummy' variables for each firm or group of firms. These variables are to account for inherent differences by firm in peak relative to off-peak energy use. These variables are defined for the m firms (m = 1,…,M): D_m = 1 if the observation is for firm m, and = 0 otherwise. It must be emphasized, however, that this is only an initial specification. By using other firm characteristics from the survey, the model can be designed to account for differences in firm-level factors directly. These factors might include, but not be limited to such things as alternative types of production processes, differences in production shifts, differences in business hours, the availability of distributed generation, the proportion of load hedged, etc.

As Schwarz *et al*. (2002) suggest, firms that have faced fixed tariffs for electricity for many years must learn how to respond to price differences between peak and off-peak periods. The efficiency should be higher the longer a firm has faced price variation. Thus, if we can obtain data on when customers were previously enrolled in some type of RTP program, we can test both the hypothesis that experience affects the overall level of peak to off-peak use, as well as the ability to shift load in response to prices (Schwartz found a modest relationship between experience and elasticity). One way to capture this effect is by defining a variable: T_{tm} = the number of months that firm m has been in the RTP program on day t. To test these separate hypotheses, this variable would have to be added as both an "intercept" shifter at this stage of the model, as well as a "slope" shifter.

Finally, the effect of daily weather on the ratio of peak to off-peak electricity use is captured through a weather index: W_{tm} = weather index for day t from the weather station nearest to firm m for which there are data.[40]

Given this set of variables, the equation to be estimated is:

(10a) $\ln [k_{ptm} / k_{otm}] = \sum_m (F_m) D_m + (w) W_{tm} + (T) T_{tm} + \{ \ln [(T_P) T_{tm} + (D_{pp}) + (D_{po}) [p_{0tm} / p_{ptm}]^{1/2} - \{ \ln [(T_0) T_{tm} + (D_{oo}) + (D_{op}) [p_{ptm} / p_{0tm}]^{1/2} \},$

where the terms in ( ) are coefficients to be estimated. We further require that T_p=T_o, and D_{po} = D_{op}, both for symmetry. We also require that $D_{oo} + D_{pp} + D_{op} + D_{po} = 1$. In this specification, it is important to note that the experience variable T_{tm} is the only firm characteristic that is included as both an intercept and a slope shifter. This was done for simplicity of exposition. The weather variable can be easily included as a slope shifter as well. The firm-level dummy variables and weather are included only as intercept shifters. By also including the firm-level dummy variables as slope shifters, one would effectively be estimating separate models for each firm. To study the effect of specific firm characteristics on electricity usage in response to price differences, this strategy would be of little use. Therefore, using other firm-level data from the survey of other sources, one can include those variables directly into the model as both intercept and slope shifters. This specification allows for direct tests of the hypotheses that certain firm-level characteristics affect price responsiveness. The specification is a decided improvement compared to accounting for firm level differences *only* through including the individual firm dummy variables. By relying only on firm-level dummy variables, one is able to measure differences in price responsiveness by firm, but we are able to say nothing about what it is about the firm that makes this so.

Attachment B: The Model with Both Within-day and Between-Day Price Response

The econometric model used to estimate both within-day and between-day price response is essentially the one used recently by Schwarz et al. (2002). They state that this model is based on a procedure in King and Shatrawka (1994), and it is a variant of the approach of Herriges et al. (1993). This model assumes a nested Constant Elasticity of Substitution (CES) functional form to characterize customer demand for electricity. Consumption within-days is weakly separable from consumption across days. This model does allow for the change in electricity use within a day in response to hourly price changes that differ from the change in electricity use between-days in response to a daily price index.[41]

---

[40] Our initial specification of the weather index is based on heating and cooling degree-days constructed from mean daily temperature and dew point values for weather stations in close proximity to NMPC SC-3A customers. The construction of the index is in Attachment C.

[41] One explanation for the lack of complete correspondences between substitution elasticities and the actual, nominal peak load reductions is that customers can shift load from the peak price day to another

Since the theory underlying this structure is outlined in Appendix E, we report only the estimating equations:

(1b) $\ln (E_{dh} / E_{th}^{g*}) = \sum_t A_t - \sigma_H \ln (P_{dh} / P_{th}^{g*}) – (\sigma_D - \sigma_H) \ln (D_d / D^{g*})$

where E_{dh} is electricity use for hour h and day d and P_{dh} is the electricity price for hour h and day d. Also $\ln E_{th}^{g*} = (1/N_t) \sum_m \sum_{d\varepsilon t} \ln (E_{mdh})$ and $\ln P_{th}^{g*} = (1/N_t) \sum_m \sum_{d\varepsilon t} \ln (P_{mdh})$ are the logarithms of the geometric means over the months m of a particular season, and $\ln (D_d / D^{g*}) = (1/2) \sum_h (w_{dh} + w_{th}^{*}) \ln (P_{dh} / P_{th}^{g*})$ is a daily price index, and $w_{dh} = P_{dh} E_{dh} / \{ \sum_k P_{dk} E_{dk} \}$ is the share of electricity expenditure for hour h on day *d* and $w_{th}^{*} = [1/N_t] [\sum_m \sum_{d\varepsilon t} w_{dh}]$ is the arithmetic mean of the electricity expenditure share for hour h in all days of type t.[42] Letting $E \equiv \ln (E_{dh} / E_{th}^{g*})$; $A \equiv \sum_t A_t$; $P \equiv \ln (P_{dh} / P_{th}^{g*})$; and $D \equiv \ln (D_d / D^{g*})$, we can make the appropriate substitutions into (1c), rearrange terms and end up with the model for estimating σ_H and σ_D:

(2b) $E = A + \sigma_H (D – P) + \sigma_D (- D)$

The *a priori* expectation for the signs of both estimated coefficients is positive. As in King and Shatrawka (1994), A is a vector of binary variables that could be used to control for any influence by days of the week, or by firm. This vector of variables represent intercept shifters, but one could also include these variables easily as slope shifters so that both σ_H and σ_D could be allowed to vary by weather or firm characteristics. For example if we include a weather index, defined by day W_D and by season W_S in a manner similar to that in the text above, as slope shifters for both hourly and between-day price response, the individual response elasticities are derived as: $\sigma_H = b_H + m_D W_D$, and $\sigma_D = b_D + m_S W_S$

After making appropriate substitutions into equation (2b) and arranging terms, we have:

(3b) $E = A + (b_H) (D – P) + (m_D) W_D (D – P) + b_D (- D) + m_S W_S (- D)$

Attachment C: Development of Weather Variables

We initially obtained historical weather data for several weather stations in NMPC's service territory from the National Climatological Data Center (NCDC) Internet site. The data set encompassed the period 01/01/2000 – 07/15/2003 and contained daily mean temperature and dew point values. These were used to calculate heating and cooling degree-days and heat indices on a daily basis.

---

day. Customers may shift load between days because of conditions specific to their industrial processes or union/labor rules related to work shifts (e.g. notification requirements). If we fully accounted for both in day and between day shifts, then some of what is being classified as conservation might be explained more logically.

[42] The expression $\ln (D_d / D^{g*})$ is the daily price index formed using a Tornqvist price index. Usage in each hour, relative to the average level, is a function of relative price in that hour and the daily aggregate price index. K-S provides the Tornqvist index in footnote 3.

Variable Construction

The following formulae summarize the calculation of the variables employed in the regression models. These are based on statistics developed by the National Weather Service. Note that the derivation of the Heat Index required several intermediate steps: a) conversion of the temperature and dew point values to Celsius; b) calculation of actual and saturation vapor pressure; and c) calculation of relative humidity. This was necessary since relative humidity (RH) was not available in the NCDC data for the analysis period; and the RH is required to calculate the heat index.

Calculation of Relative Humidity

Tf = Mean temperature (FE)
Tdf = Mean dewpoint temperature (FE)
Mean temperature (CE) = Tc = 5/9 * (Tf - 32)
Mean dewpoint temperature (CE) = Tdc = 5/9 * (Tdf - 32)
Actual Vapor Pressure = E = $6.11*10.0^{(7.5*Tc / (237.7+Tc))}$
Saturation Vapor Pressure = Es = $6.11*10.0^{(7.5*Tdc / (237.7+Tdc))}$
Relative Humidity (%) = RH = (E/Es) * 100

Calculation of Degree-Day Indices

Heating degree-days (Base 65)(HDD65)
if Tf >=65, HDD65 = 0
if Tf <65, HDD65 = 65 - Tf
Cooling Degree-Days (Base 65) (CDD65)

- if Tf <=65, CDD65 = 0
- if Tf >65, CDD65 = Tf – 65

Heat Index (HI70)

if Tf <=70, HI70 = Tf
if Tf >70, HI70 = - 42.379 + 0.04901523*Tf + 10.14333127*RH- 0.22475541*Tf*RH
- $(6.83783*10^{-3})*(Tf^2)$ - $(5.481717*10^{-2})*(RH)$ + $(1.22874*10^{-3})*(Tf^2)*(RH)$
+ $(8.5282*10^{-4})*Tf*(RH^2)$ - $(1.99*10^{-6})*(Tf^2)*(RH^2)$.