EVALUATION OF CALIFORNIA'S REAL-TIME ENERGY METERING (RTEM) PROGRAM

CONSULTANT REPORT

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EXECUTIVE SUMMARY

Background

In March 2001, the California Assembly (in AB29X) authorized $35 million to install advanced automatic meter reading (AMR) devices for all customer accounts with peak demands greater than 200 kilowatt (kW) in the state. The funding was administered by the California Energy Commission (CEC), which decided to install metering systems capable of recording hourly interval data, and communicating the data remotely to the utilities on a timely basis, so that each customer's daily load data could be made available to them on a secure website.[1]

Approximately 25,000 real-time energy meters (RTEM) were installed across the state – nearly half (12,000) at Southern California Edison (SCE), and more than a quarter (7,800) at Pacific Gas & Electric (PG&E). San Diego Gas & Electric (SDG&E) had already received commission approval to install advanced meters for customers in the 100 to 300 kW range, so it used Energy Commission funding to install approximately 1,400 meters for customers > 300 kW. The remaining meters were installed at municipal utilities, including Los Angeles Department of Water and Power (LADWP), with 3,400, Sacramento Municipal Utility District (SMUD), with 300, and the Southern California Public Power Authority (SCPPA) and Northern California Power Agency (NCPA), which together received approximately 350.

Most of the eligible customers—for the most part, those with maximum demand in excess of 500 kW—already faced time-of-use (TOU) energy prices. However, those that did not were converted to a new version of their standard tariff which converted flat energy prices to TOU energy prices. Customers were also provided a package of information with instructions for accessing a website to obtain timely information on their hourly electricity consumption and methods for taking advantage of that information. Each utility designed its own website.

The metering expenditures were approved during a period of crisis in the state's electric power industry, and the original intent of the metering was to support the development of real-time pricing (RTP) rate designs, influence customer electricity usage patterns, and encourage demand response, particularly during periods of high wholesale costs. To date, no extensive RTP programs have been approved. However, some pilot demand response programs have been implemented, and the metering infrastructure is now in place to offer customers a variety of possible dynamic pricing and demand response programs. Furthermore, the RTEM customers now have access to timely information on their electricity usage.

[1] Most customer accounts with maximum demands greater than 500 kW already had interval meters installed in their facilities. However, many needed upgrades to install the communication equipment needed to allow remote data retrieval and posting on the website.

This report documents results of a qualitative and quantitative evaluation of the RTEM program. The *qualitative* evaluation was designed to develop "lessons learned" about the metering technologies, the installation process, the communication of information to customers, and customers' perception and use of the timely information on their energy usage patterns. The *quantitative* evaluation was designed to measure any changes in customers' energy consumption that can be attributed to the installation of the meters, the availability of new information on their energy usage patterns, and/or the conversion to a TOU price structure. Analyses were conducted on metered usage data for each of the three investor-owned utilities in the state, Southern California Edison (SCE), Pacific Gas & Electric (PG&E), and San Diego Gas and Electric (SDG&E).

Qualitative Evaluation

Information for the qualitative evaluation was obtained through telephone interviews with utility project managers and customer account executives. Research topics included customer perception of the meter installation process, the information package provided by their utility, the instructions for accessing their data on the website, customers' use of their energy usage information, and any load-change actions they report having taken.

Christensen Associates conducted telephone interviews with the RTEM program managers at each of the utility organizations that participated in the RTEM program. These included the three major privately-owned utilities, the two large municipal utilities (LADWP and SMUD), and SCPPA and NCPA. The interviews were conducted using an open-ended discussion guide that was designed to allow the respondents to tell their story about their participation in the RTEM program. The primary purpose of these interviews was to identify "lessons learned" by program administrators.

Our interviews with the utility project managers produced information on their views on the RTEM project overall objectives, their perspective on customers' reactions to the meters, the access to usage data via website, and any roadblocks they experienced in implementing the project.

Perceived Program Motivation and Goals

Nearly all respondents identified difficulties in the California power markets during 2000/2001 as the driving factor behind the establishment of the RTEM program. Many of the respondents mentioned their experience with earlier Energy Commission efforts to implement demand response programs for large commercial and industrial customers, and believed that the previous effort helped them in accomplishing the RTEM project. The previous Energy Commission program allowed utilities to develop expertise in understanding and implementing advanced metering programs, including familiarity with metering and communications technologies, and familiarity with potential vendors.

Respondents typically fell into two groups when discussing perceived project goals. One group tended to define the project goals in terms of accomplishing the specified number of interval meter installations and fulfilling the terms of the contract with Energy Commission. The other group of respondents tended to define the project goals in terms of enhancing customers' ability to optimize their electricity use.

Reported Customer Uses of Metered Data

Most respondents were only able to provide limited specific examples of customers taking advantage of the capabilities of the websites and access to their usage data. In some cases, respondents were aware of specific actions undertaken by the customers, but in most cases they indicated that they had only second-hand knowledge of customers' use of the usage data.

While the respondents were able to cite some specific examples of how customers were using the data collected by the interval meters, most respondents indicated that it appears that many customers do not actually use the website to obtain usage data. Other comments reflected some doubts about customers' use of the interval data, or occasional technical problems in implementing the website.

We also conducted interviews with several key-account representatives at three of the utilities to obtain a perspective on RTEM customer reactions to the program—in particular how customers were reacting to access to electricity usage data collected by the interval meters. In general, the interviews with customer account executives confirmed what was heard during the project manager interviews. Many customers receiving meters appeared to be relatively indifferent to the RTEM program. This indifference could be explained in terms of two factors: Either customers didn't perceive significant benefits from intensively monitoring their energy usage, or they weren't aware of how the usage data might be used to reduce their electricity costs.

When asked about customer usage of the website, the account executives indicated that to the best of their knowledge most customers did not visit the website to collect and analyze usage data. For the smaller number of customers who the account executives believe do access the data, they indicated that intensity of use of the website varied across customers. Some customers visited frequently (for example, daily or weekly), while others only viewed their usage data on a less frequent basis. The account executives were able to identify specific instances in which RTEM customers were able to use load data to reduce demand charges and to tie energy usage patterns to specific processes or equipment use.

SCE Survey Results

While not an explicit component of our RTEM evaluation, SCE allowed us to leverage off of their customer survey of EnergyManager users and non-users regarding customers' stated uses of the website tools. SCE asked several questions regarding the usefulness of their EnergyManager website for a variety of tasks, including shifting energy consumption or peak demand away from peak periods, and reducing energy costs. Approximately 40 percent of the respondents reported that they had used EnergyManager to take each of the actions asked about, including the following:

Shifting energy <u>usage</u> away from On-peak hours
Shifting energy <u>demand</u> away from On-peak hours
Reducing overall <u>energy</u> usage
Reducing energy <u>demand.</u>

In addition, about 50 percent of the respondents reported "reducing costs," and 30 percent reported installing energy efficiency equipment as a result of using EnergyManager.

Lessons Learned

Many aspects of the RTEM program were unique due to the extremely tight timeline imposed by the crisis atmosphere that produced the program in the first place. However, some general conclusions regarding lessons learned may be drawn from the respondents' comments. First, close attention should be paid to the testing of the interface between the meters, the communications system, and the utility data management system to avoid difficulties during rollout.[2]

Second, the apparent concerns on the part of at least some customers about being transferred to a TOU rate suggest an area of concern if a similar type of metering project were to be undertaken for groups of smaller customers. Mandatory assignment to TOU tariffs would likely cause bill increases for some customers unless modifications to the rate design were made to insure some degree of revenue neutrality at each customer's pre-participation pattern of electricity usage.

Quantitative Evaluation

Customer Data

SDG&E, SCE and PG&E each provided monthly billing data and/or interval load data to the project. SDG&E and PG&E provided data for all eligible customers for whom data were available. SCE provided load and survey response data for a sample of approximately 300 customers who participated in a telephone survey in May 2003 regarding their use of SCE's EnergyManager website. SCE and PG&E also provided some data on individual customer use of their respective websites. Most of the analysis in the project focused on the SCE and PG&E data. We conducted a preliminary analysis of monthly billing data for SDG&E customers.

Analysis Approach

The overall objective of the quantitative evaluation was to measure changes in consumer load patterns that can be attributed to the immediate access to information on their usage patterns through the RTEM websites, and/or the switch to TOU pricing, for those smaller customers who faced new TOU energy prices. However, achieving this objective was made difficult by a number of technical challenges. The fundamental challenge was the fact that the RTEM project was not implemented through an experimental design, with a "control" situation to serve as a reference point for comparing consumers' usage after receiving the RTEM equipment. That is, a typical quantitative evaluation of a public policy program or action involves a control group situation, represented, for example, by conditions prior to implementing the program, or a control group of customers that are not subjected to the program.

In contrast, the RTEM project involved installing equipment for *all* available customer accounts, thus implying very limited control situations, as indicated by the following features:

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[2] Details on the technologies involved, and the implementation and validation process may be found in "Real Time Metering Program: Report to the Legislature on Assembly Bill 29X," California Energy Commission, P400-02-004F, June 2002.

- All eligible customers were provided with RTEM equipment, leaving no contemporaneous control group of non-participating customers.
- All large customer accounts of size > 500 kW already faced TOU energy prices and were not changed to a new rate.
- All smaller customer accounts were switched to a TOU energy rate, leaving no contemporaneous control group of similar customers remaining on flat rates.
- For the smaller customer accounts that were switched to a TOU rate, no TOU energy consumption data existed prior to their receiving the RTEM meters and being switched to TOU pricing (except for existing load research accounts at PG&E).
- Even in the absence of TOU energy prices, PG&E and SCE customers faced summer demand charges that gave customers an effective TOU price signal during periods of their highest loads. Furthermore, the Peak/Off-peak price ratio for the new TOU energy prices was relatively low, implying that the incremental TOU energy price signal sent to the smaller customers was relatively weak.
- Finally, even in cases where consumption data were available for time periods prior to installation of the RTEM equipment (*e.g.*, load data for PG&E's E-19 customers, who were metered and faced TOU energy prices prior to RTEM, and for their load research sample of A10 customers), the prior period was represented by 2000 and/or 2001. These were periods in the midst of and shortly after the California energy crisis, in which consumers were strongly encouraged to reduce consumption, especially during summer peak periods, regardless of the price, and thus highly non-representative for use as a reference period. .

Given the lack of a traditional comparison period or control group, we were forced to turn to other methods of defining a "change" situation in which consumers' usage in one period could be compared to another to draw inferences about the effect of RTEM and the new TOU rates. We relied largely on the fact that the SCE and PG&E TOU rates differentiated strongly between the *summer* and *non-summer* months (defined as June through September for SCE, and May through October for PG&E). Thus, for example, we analyzed differences between consumers' average energy consumption during the *summer* peak period hours, in which they faced the highest demand and energy charges, and their consumption during the same time periods in the *non-summer* months (after controlling for weather differences), in which demand and energy charges were lower. We interpreted significant differences in usage during these time periods as evidence of customer response to TOU price differences. For most customers, it was difficult to detect significant weather-adjusted peak load changes between summer and non-summer months. However, as summarized below, a significant fraction of most of the customer types examined (*e.g.*, by size and Standard Industrial Classification (SIC) category) showed evidence of load reductions in, or load shifting away from summer peak periods.

We calculated these load changes using econometric analysis of customer energy usage by TOU period that used variables indicating the summer peak TOU period to help explain changes in usage. We also illustrated the nature of customers' TOU response using graphical comparison of average summer and non-summer loads, some of which confirm cases of price responsive behavior.

We developed estimates of TOU price response on both an *average* basis for various groups of customers (*e.g.*, by rate class and SIC group), using pooled regression analysis, and an *individual customer* basis to explore the distribution of price responsiveness across customers. This approach to estimating TOU price is somewhat crude and atypical. A preferred approach would have been to have observations on customers' summer peak usage under two or more alternative price scenarios. However, as noted above, no such conditions were available in this case.

One way to characterize our research problem is that of trying to find the *signal* of TOU price response in the *noise* of changes in consumers' peak-period usage on summer and non-summer days due to a variety of factors, including weather, seasonal usage patterns and TOU prices. When the price signal was strong, as evidenced by a substantial reduction in summer peak usage relative to both usage during the same period in non-summer months and average summer daily usage, then the regression coefficients typically indicated such patterns unambiguously (we include graphs of illustrative customer loads that demonstrate examples of clear TOU price response). However, when the signal was weak relative to the noise, such as when consumers' usage varied considerably for reasons likely other than the non-summer to summer peak price change, then the coefficients provided less ability to identify actual price-responsive behavior.

We analyzed data for two general categories of customers at SCE and PG&E which differed by rate class. Both utilities offered one default rate for commercial and industrial customers less than 500 kW (GS2T for SCE and A10 for PG&E), whose tariff prices were similar. SCE also offered a default rate for commercial and industrial customers greater than 500 kW (TOU-8), while PG&E offered separate rates for customer accounts between 500 and 1,000 kW (E19) and those greater than 1,000 kW (E20). The seasonal price patterns for the larger accounts differed somewhat more between utilities than those for the smaller accounts, as described below.

TOU Prices

Tables ES1 and ES2 illustrate the differences in the tariff demand and energy charges for the two general types of customers at the two utilities. To understand the price incentives inherent in utility tariffs that contain both *demand* and *energy* charges, however, it is instructive to combine the charges into a single measure of customers' *effective energy charge* (EEC) during particular time periods. EECs indicate the implied change in a customer's monthly bill for a unit change in consumption in that time period. They effectively allocate demand charges over time periods in a month in proportion to the likelihood of incurring an additional demand charge in those periods.

Figures ES1.a and b illustrate hourly EECs for a typical weekday for SCE's GS2 (with and without the TOU energy prices) and TOU-8 tariffs respectively, for the summer and non-summer months. Figures ES2.a and b show similar patterns for PG&E's A10 and E19 tariffs. The figures illustrate two key features of the rates for both utilities. First, customers' effective price of electricity during the hours defined by the summer peak period are substantially higher during the summer than during the same period in non-summer months, for both sets of tariffs. Second, the conversion to TOU energy prices had only a modest effect on GS2T and A10 customers' effective price during the summer peak period; they already faced an effective TOU price signal due to the summer demand charge.

Table ES1. SCE Tariffs
(Summer = June – September)

	GS2 Summer	GS2 Winter	GS2T Summer	GS2T Winter	TOU-8 Summer	TOU-8 Winter
Demand charges ($/kW)						
All hours	$ 5.40	$ 5.40	$ 5.40	$ 5.40	$ 6.60	$ 6.60
Seasonal	$ 7.75		$ 7.75			
On-peak					$ 17.95	
Mid-peak					$ 2.70	
Non-TOU energy charges ($/kWh)						
First 300 kWh/kw of Max demand	$ 0.119					
Additional kWh	$ 0.135					
TOU energy charges ($/kWh)						
On-peak (Hrs 13 - 18)			$ 0.179	$ -	$ 0.132	
Mid-peak			$ 0.122	$ 0.130	$ 0.054	$ 0.065
Off-peak			$ 0.106	$ 0.106	$ 0.035	$ 0.036

Table ES2. A10 and E19 Energy and Demand Charges

	A10 Summer	A10 Winter	A10 TOU Summer	A10 TOU Winter	E19 Summer	E19 Winter
Demand charges ($/kW)						
All hours					$ 2.55	$ 2.55
Seasonal	$ 6.70	$ 1.65	$ 6.70	$ 1.65		
On-peak					$ 13.35	
Mid-peak					$ 3.70	$ 3.65
Non-TOU energy charges ($/kWh)	$ 0.160	$ 0.112				
TOU energy charges ($/kWh)						
On-peak (Hrs 13 - 18)			$ 0.195		$ 0.188	
Mid-peak (8:30 - 12; 6 - 9:30)			$ 0.152	$ 0.115	$ 0.109	$ 0.115
Off-peak			$ 0.144	$ 0.108	$ 0.092	$ 0.092

Figure ES 1.a SCE GS2T Effective Energy Charges (before and after change to TOU energy prices)

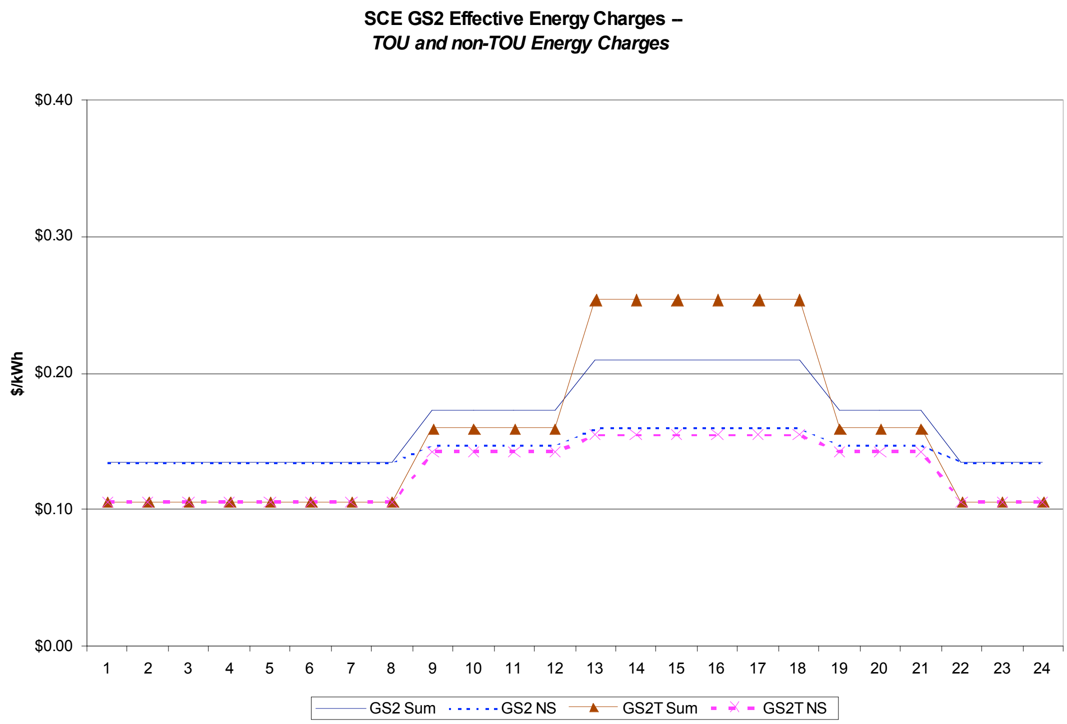


Figure ES 1.b SCE TOU-8 Effective Energy Charges

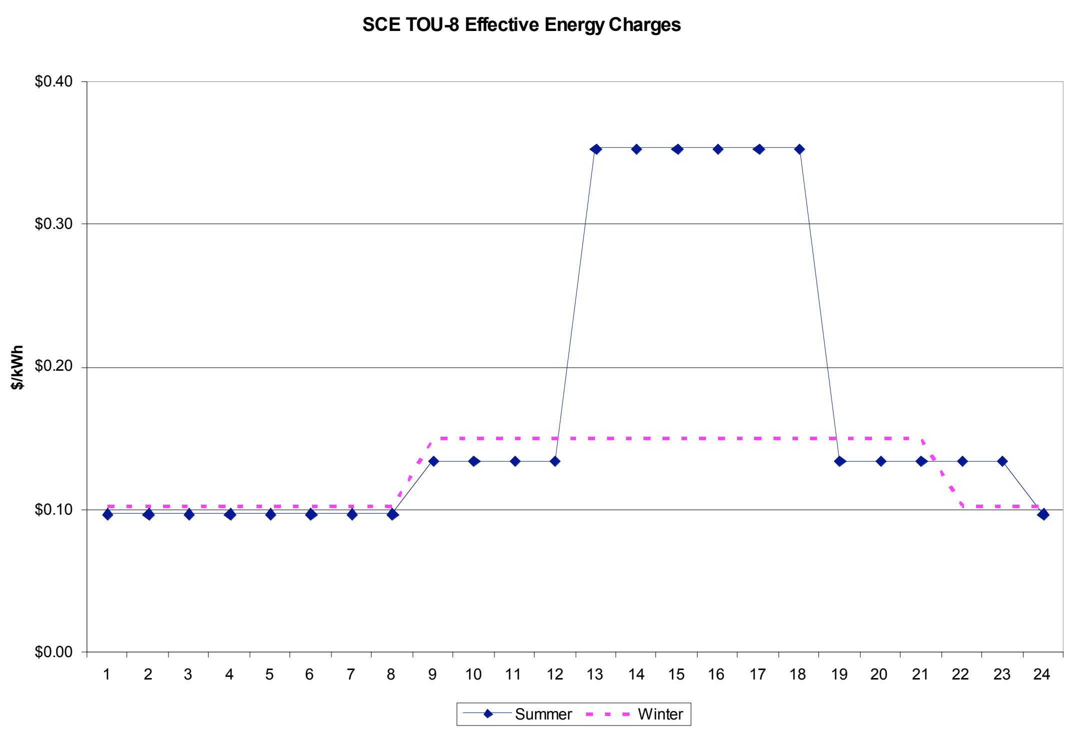


Figure ES 2.a PG&E A10 Effective Energy Charges

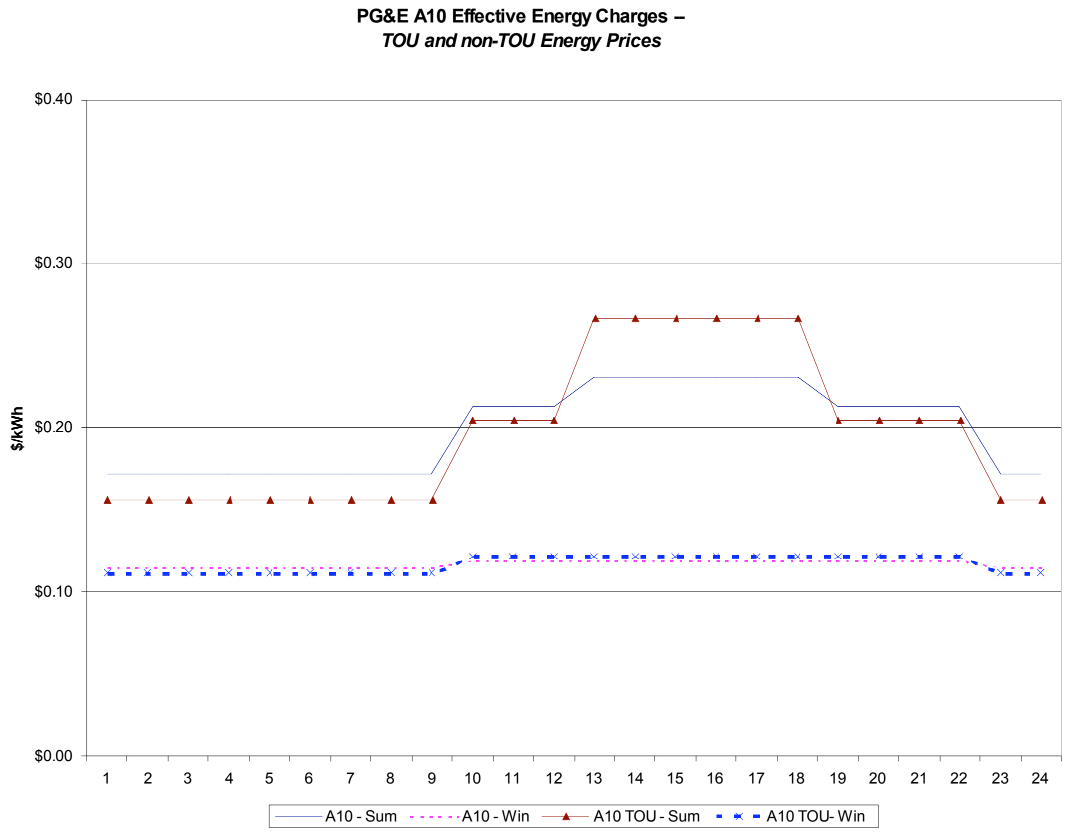
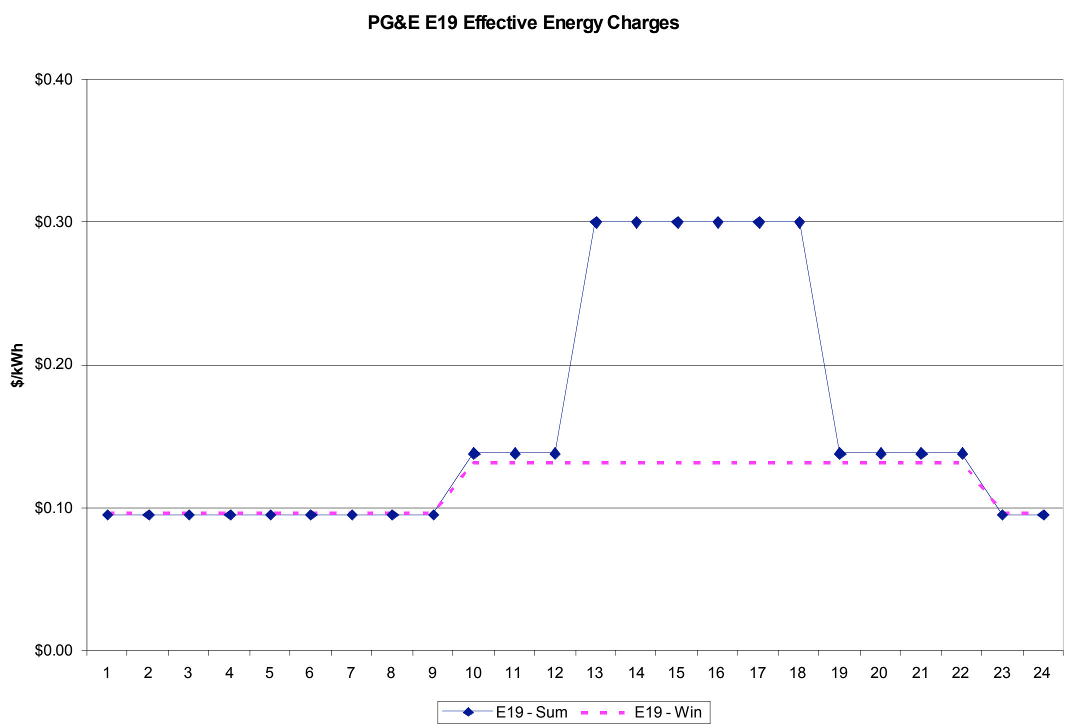


Figure ES 2.b PG&E E19 Effective Energy Charges



TOU Price Response Results

SCE Results

The results of our analysis of TOU price response for the SCE customers may be summarized as follows:

1. The TOU-8 customers on average responded in significant and substantial degrees to the higher energy and demand charges that they face in the summer peak time period relative to other time periods of the year. They reduced average usage in the summer peak period relative to usage in other summer time periods and in the same period in non-summer months.
2. Industrial customers (those in the manufacturing SIC codes between 2 and 3, and those in SIC 4, which includes water and sewer utilities that have potentially flexible loads) showed greater price responsiveness than Commercial customers (those in SIC codes between 5 and 7, including retail stores, office buildings and service industries), which is as expected.
3. Some GS2T customers reduced relative usage in the summer peak period in significant but modest degrees. However, it is not possible to definitively attribute those load changes to the relatively small TOU peak-period energy price differential that they faced *after* receiving the RTEM equipment, as they already faced an implicit higher price during their own summer peak periods due to the summer demand charge that applied before and after the change to TOU energy prices (and data were not available in the prior period). Like the TOU-8 class, Industrial customers were more price responsive than Commercial customers.
4. There is some evidence that cumulative use of the SCE EnergyManager website was associated with lower average daily consumption among GS2T customers. However, this lower daily usage did not necessarily imply reductions in the peak period.
5. It is difficult to draw conclusions about any systematic change in price responsiveness between 2002 and 2003, such as might be expected from longer experience facing the TOU energy prices (for GS2T customers) or taking advantage of the EM website tools.
6. The individual customer price responsiveness results indicate that the percentage of price responsive customers ranged from 20 to 30 percent of the GS2T customers, and 30 to 50 percent of the TOU-8 customers in the broad SIC groupings.

In summary, we found evidence in the interval load data of customer response to TOU prices, particularly in the case of the large summer peak-period price premium for TOU-8 customers, and also to a lesser extent for the smaller GS2T customers, who faced a weaker TOU price signal. There is also evidence from the SCE survey that a large fraction of the survey respondents reported using the EM website to help them take actions to reduce on-peak usage.

However, given the lack of before-period usage data, or usage for a control group of comparable customers that did not receive the RTEM equipment or receive TOU prices, we cannot attribute the TOU price response behavior observed in the data to the installation of the RTEM equipment. The large summer peak prices faced by the TOU-8 customers existed prior to the RTEM installations, implying that the observed peak-period load reductions were occurring previously. Furthermore, there is no strong evidence that access to the EM website enhanced their price responsive behavior. There is similarly little evidence that GS2T customer use of the EM website led to significant changes in peak-period usage.

PG&E Results

The results of our analysis of TOU price response for the PG&E customers may be summarized as follows:

1. The pooled analysis found relatively little evidence of peak-period TOU price response on average for the A10 class, moderate price response for the E19 class, and substantial price response for the E20 rate class (customers between 1,000 and 5,000 kW).
2. For the most part, only for some SIC groups, particularly the manufacturing SICs of 2 and 3, and SIC 4, and primarily for the larger customer classes, were significant price response coefficients estimated.
3. The individual customer analysis demonstrated that at least some fraction of customers in nearly all SIC groups (ranging from 10 to 20 percent) evidenced significant peak-period TOU price response in 2002 and 2003, while an additional comparable fraction appeared to respond in limited and not statistically significant ways.
4. Results for 2001 indicated substantially greater degrees of TOU price response in the summer peak period in nearly every rate class/SIC group, compared to their responsiveness in the subsequent years.
5. Our analysis of the effect of customer use of PG&E's InterAct website software found limited evidence of changes in consumer price response, suggesting that customers in at least two of the A10 SIC groups increased their peak period price response after establishing an InterAct account.

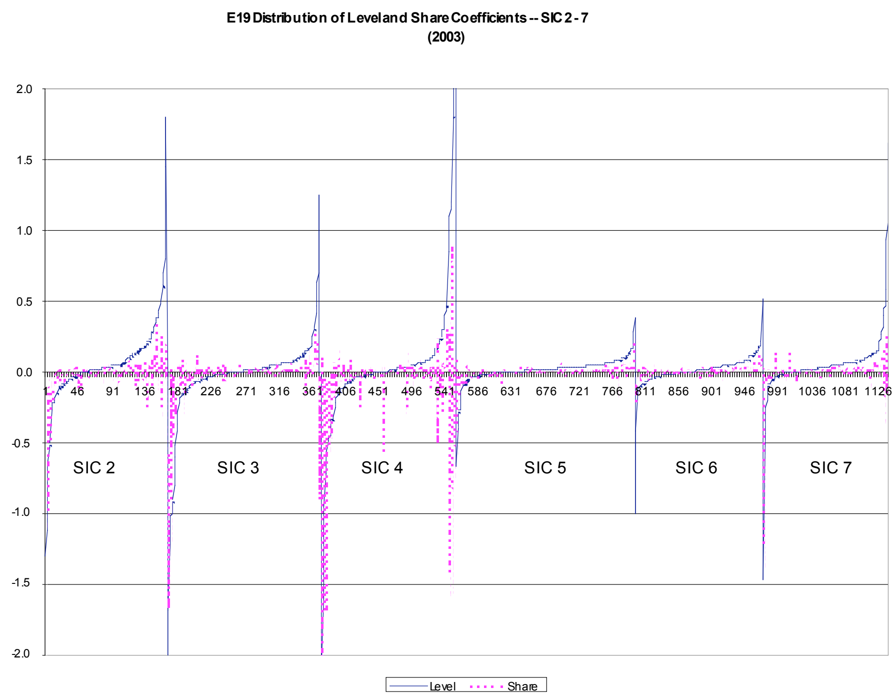
Individual Customer TOU Price Response

Figure ES 3 illustrates the findings from the analysis of individual customer TOU price response. It shows the distribution of the estimated summer peak period coefficients for some 1,100 of PG&E's E19 customer accounts, sorted by SIC group and the summer TOU peak period *level* coefficient. They also show the corresponding *share* equation coefficient. The SIC groups are in order from left to right (*e.g.*, the left-most distribution is for SIC 2 manufacturing accounts and the far right distribution is for SIC 7 services).

We interpreted negative values on the coefficient of either summer peak energy usage or energy share as potentially indicative of TOU price response (in the majority of cases, the sign was the same on both coefficients). A negative coefficient in the level equation, combined with a negative coefficient in the share equation, indicates that peak period usage in the summer months actually falls relative to non-summer months after controlling for weather, and is distinct from overall usage changes. It is a rather clear indication that the peak reduction is due to the high peak-period prices.[3] Peak period load reductions may also occur even with positive or insignificant coefficients in the share equation, depending on the relationship between the reduced peak load and the average summer daily load.

[3] The form of the estimating equations implies that the coefficients represent percentage changes, where values greater than -1.0 are possible due to the logarithmic form of the equation, and typically represent peak load reductions of nearly 100%.

Figure ES 3. Distribution of Individual Customer Coefficients – E19



The following observations may be made about the price response distributions:

- In nearly every SIC group, approximately thirty to forty percent of the level equation coefficients are negative, suggesting some degree of TOU price response;
- In nearly every SIC group, approximately 10 percent of the customer accounts show evidence of strong price responsiveness, suggesting summer peak load reductions of 20 percent or more, with the larger customer accounts in SIC 2 through 4 showing the largest load reductions.

Aggregate TOU Price Response

We used the estimated coefficient results from the SCE and PG&E individual customer regressions to develop estimates of aggregate TOU price response at the rate class and utility level. To do so, we needed to make a number of assumptions and approximations regarding both the treatment of the estimated price response coefficients and the method for scaling results to the population level for the industry types represented in the analysis. In the case of SCE, we used aggregate population-level data on customer accounts and sales to scale up from the sample customers used in the analysis. In the case of PG&E, the portion of the population of customers that was used in the analysis was quite high, making it relatively easy to scale up the total, as indicated by available billing data (the population totals excluded *direct access* customers served by other suppliers).

We used a relatively conservative screening rule for determining how to apply the estimated price response coefficients to calculate an implied amount of summer peak-period load reduction. Specifically, we calculated load reductions only for those customer accounts for which estimated summer peak-period coefficients indicated unambiguous peak load reductions. Use of this screen may have excluded an unknown number of small TOU peak load reductions that could not be distinguished from non-price induced load variations.

The resulting estimated aggregate loads and TOU peak load reductions are shown in Table ES 3 for each rate class and utility, and separately for industrial and commercial customers. For PG&E, the estimated TOU peak period load reductions amounted to 3.4, 10 and 19.6 MW respectively for the three rate classes, totaling approximately 33 MW. These load reductions represented from 1 to 3.4 percent of the total class loads.[4]

For SCE, we estimated that the GS2T customers reduced their summer peak usage in 2003 by 1.8 percent, or approximately 23 MW, while the TOU-8 customers reduced their summer peak usage by 7.5 percent, or 142.5 MW. Given the relatively small sample size of the TOU-8 industrial group (approximately 30) and the resulting uncertainty about whether the several extremely price responsive customers in the survey sample were truly representative of the population, we suggest that the estimate for that group in particular be regarded as having a fairly wide band of uncertainty.

Conclusions and Implications

The primary conclusion of this evaluation is that a significant fraction of large industrial customers in California and, to a lesser extent, commercial and smaller industrial customers, reduce their summer peak period electricity consumption in the face of existing summer peak TOU demand and energy charges. However, we were able to find only modest evidence that any of these load reductions have been caused or enhanced by the installation of the RTEM equipment and conversion of smaller customers to TOU energy prices. This lack of hard evidence of RTEM effects is possibly due in large part to the evaluation difficulties imposed by the non-experimental nature of the program, and the lack of comparison period or control group data. This resulted in the use of a relatively unorthodox analysis approach that likely only captured large and unambiguous TOU price response, and was unable to discern potential incremental effects of the RTEM equipment and consumers' web-based access to usage data.

[4] These estimates do not include data for customers in agricultural operations, SIC 8 (including hospitals and schools) and 9 (Government), or E20 customers larger than 5,000 kW.

Table ES 3. Aggregate TOU Peak Load Response

PG&E	Ave. Peak Demand (MW)	Estimated TOU peak reduction	% Reduction
A10			
Industrial	122	2.5	2.1%
Commercial	178	0.8	0.5%
Total	300	3.4	1.1%
E19			
Industrial	291	8.6	3.0%
Commercial	318	1.3	0.4%
Total	609	10.0	1.6%
E20 (< 5 MW)			
Industrial	399	18.1	4.5%
Commercial	178	1.5	0.9%
Total	576	19.6	3.4%

SCE	Ave. Peak Demand (MW)	Estimated TOU peak reduction	% Reduction
GS2T			
Industrial	783	19.2	2.4%
Commercial	479	3.5	0.7%
Total	1,263	22.7	1.8%
TOU-8			
Industrial	743	119.4	13.8%
Commercial	1,007	23.1	2.2%
Total	1,750	142.5	7.5%

Industrial = SIC 2 - 4
Commercial = SIC 5 - 7

The evidence of TOU price response that was found in the study, however, has one important implication regarding the topic of demand response in California. That is, the results suggest that a number of SCE and PG&E commercial and industrial customers, particularly industrial customers larger than 500 kW, already respond to the substantial peak period price differential of more than 2 to 1 between summer (June through September for SCE, and May through October for PG&E) and non-summer months. These are presumably the customers whose loads are most flexible, and for whom electricity costs are most sensitive, as their peak-period load reductions and load shifting have to take place every weekday for four to six months of the year to achieve full savings. Our analysis of individual customer price response indicates that some customers in SIC 2 through 4 are able to reduce summer peak load levels by amounts ranging from 5 percent to nearly 100 percent. These estimates are confirmed by average daily load profiles examined for a number of representative price-responsive customers.

The TOU price response results suggest that little additional demand response can be provided currently by these customers who already respond strongly to the standard tariffs' TOU demand and energy charges. However, these customers would be perfect candidates for a version of a *critical peak pricing* product that sent high peak prices only on days with critical resource constraint conditions, and lower peak prices on lower-cost days. These customers could continue to provide substantial demand response on days on which it was most valuable, but could take advantage of lower peak prices on days of lower cost by not having to modify their operations.

A recent Working Group 2 evaluation of demand response programs calculated that customers could achieve bill savings of 1 to 2 percent by participating in demand response programs, and questioned whether that would provide sufficient incentives for customers to participate.[5] Our analysis of potential bill savings from a range of summer peak load reductions comparable to those found in this study, given PG&E's standard TOU tariffs, indicated bill savings in the range of 1 to 5 percent. Thus, the findings from the present study indicate that some 10 to 20 percent or more of customers have already decided that bill savings of those magnitudes are sufficient incentive to take actions to reduce their peak load during the summer months, and that the aggregate peak load reductions (*e.g.*, 33 MW for PG&E and potentially as much as 165 MW for SCE) represent a significant portion of the amount suggested in the WG2 report as a reasonable potential for Demand Response (DR) programs.

However, these findings also suggest a likely reason for the minimal response to the Critical Peak Price (CPP) and demand bidding programs discussed in that report. That is, the very type of large flexible customers that should be attracted to such programs have likely already exhausted their potential peak period load response, and would have trouble squeezing out any more load response from their operations, particularly in return for payments (*e.g.*, $0.15/kWh) that are less than the effective TOU prices they already face.

[5] "Working Group 2 Demand Response Program Evaluation – Program Year 2004," prepared for WG2 Measurement and Evaluation Committee, by Quantum Consulting Inc. and Summit Blue Consulting, LLC, December 2004.

INTRODUCTION

In March 2001, the California Assembly (in AB29X) authorized $35 million for the purpose of installing advanced automatic meter reading (AMR) devices for all customer accounts with peak demands greater than 200 kW in the state. The original design for the real-time energy metering (RTEM) program was to fund meter installations only for the three major privately-owned utilities. However, the program was ultimately expanded to include municipal and other public utilities. The funding was administered by the California Energy Commission (CEC), which decided to install metering systems capable of recording hourly interval data, and communicating the data remotely to the utilities on a timely basis, so that each customer's daily load data could be made available to them on a secure website.[6]

Most of the eligible customers—for the most part, those with maximum demand in excess of 500 kW—already faced a time-of-use (TOU) tariff. However, those that did not were converted to a new version of their standard tariff that contained TOU energy prices. Customers were also provided a package of information by their respective utility with instructions for accessing a website to obtain timely information on their hourly electricity consumption and methods for taking advantage of that information. Each utility designed its own website.

The metering expenditures were approved during the period of crisis in the state's electric power industry, and the original intent of the metering was to support the development of real-time pricing (RTP) rate designs, influence customer electricity usage patterns, and encourage demand response, particularly during periods of high wholesale prices. To date, no RTP program has been approved. However, the RTEM customers now have access to timely information on their electricity usage and are able to participate in a voluntary Critical Peak Pricing (CPP) rate, a Demand Bidding Program, and a Demand Reserves Partnership program. Furthermore, hearings are under way at the California Public Utilities Commission on the development of a default CPP rate for large customers.

This report documents results of a qualitative and quantitative evaluation of the RTEM program. Section 2 provides an overview of the RTEM project. The *qualitative* evaluation, described in Section 3, was designed to develop "lessons learned" about the metering technologies, the installation process, the communication of information to customers, and customers' perception and use of the timely information on their energy usage patterns. The *quantitative* evaluation was designed to measure any changes in customers' energy consumption that can be attributed to the installation of the meters, the availability of new information on their energy usage patterns, and/or the conversion to a TOU price structure. Analyses were conducted on metered usage data for each of the three investor-owned utilities in the state, Southern California Edison (SCE), Pacific Gas & Electric (PG&E), and San Diego Gas and Electric (SDG&E). The SDG&E analysis is summarized in Section 4. Sections 5 and 6 document the SCE and PG&E analyses. Conclusions are offered in Section 7.

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[6] Most customer accounts with maximum demands greater than 500 kW already had interval meters installed in their facilities. However, many needed upgrades to install the communication equipment needed to allow remote data retrieval and posting on the website.

OVERVIEW OF RTEM PROGRAM

Approximately 25,000 real-time energy meters were installed across the state. Nearly half of the meters (12,000) were installed at Southern California Edison (SCE), and more than a quarter (7,800) at Pacific Gas & Electric (PG&E). San Diego Gas & Electric (SDG&E) had already received commission approval to install advanced meters for customers in the 100 to 300 kW range, so it used CEC funding to install approximately 1,400 meters for customers > 300 kW. The remaining meters were installed at municipal utilities, including Los Angeles Department of Water and Power (LADWP), with 3,400, Sacramento Municipal Utility District (SMUD), with 300, and the Southern California Public Power Authority (SCPPA) and Northern California Power Agency (NCPA), which together received approximately 350.

Details on the metering and communication systems used in the project, the implementation of the real-time metering project, and the verification of installations are provided in a CEC report, "Real-Time Metering Program: Report to the Legislature on Assembly Bill 29X," June 2002 (P400-02-004F). Briefly, the real-time meters use digital technology to record energy usage in at least 15-minute intervals, store the collected data internally, and communicate the stored readings to the utility through one of several technologies. Most commonly used were paging systems used during overnight hours when other communication traffic is minimal. The systems can typically store data for up to thirty days. However, one of the objectives of the project was to provide consumers with timely access to their usage data. Thus, the utilities designed systems by which the meters were polled each night, and data for the previous day made available each day on a website.

Website Features

Each utility designed its own unique website interface. The primary functions of the websites include viewing load data for particular time periods, comparing load data for a particular account (meter) across various possible days or time periods, or for a selected set of accounts across a particular time period, and downloading data and reports to a user's own computer. PG&E's website serves as a useful example. Early every morning, PG&E downloads data in 15-minute intervals for each RTEM customer for the previous day. After registering for an account number, customers may view their load data via a Time Interval Report tool, which uses drop-down menus to allow customers to select a meter and report interval. For more comprehensive analysis, customers can use the Multi-Point Trend Report to compare data for multiple meters and time periods, and also show temperature conditions.

Multiple Meter Issue

One issue that arose midway through the implementation of the equipment involved the definition of "customer" in terms of the size criterion used to determine when metering equipment would be installed. Indications are that the legislature and the project planners had in mind a customer as representing a single building or facility whose total load exceeded 200 kW at its maximum point. However, in dealing with meters and billings, utilities traditionally view "customers" as "meters," or "accounts." That is, they maintain records of energy usage recorded by individual meters, which correspond to different accounts, and bill each account separately. Thus, if a particular "customer" has a facility that for technical reasons has more than one meter installed, they will have more than one account, and the utility will treat each account separately.

In developing their estimates of the number of meters to be installed, they used information on accounts with maximum demands exceeding 200 kW.

As a result, customers with multiple meters/accounts at particular facilities experienced several possible situations, including the following:

- A customer site with two accounts, each with maximum demand exceeding 200 kW would receive a meter for both accounts,
- A customer site with two accounts, one with maximum demand exceeding 200 kW and one less than 200 kW would receive only one meter, and thus have access to data for only a portion of their total load, and
- A customer site with two accounts, each with maximum demand less than 200 kW would receive no meters.

As indicated in the qualitative evaluation below, some customers of the second type expressed interest in obtaining meters for all of their accounts. Customers of the third type are presumably somewhat rare. Discussions remain underway about the value of expanding advanced metering equipment installation to smaller customers.

Time-of-Use Pricing

As noted above, one condition of the project was that customers receiving the RTEM equipment who did not already face TOU energy prices were moved to newly-created TOU versions of their existing standard tariff (*e.g.*, GS2 for SCE, and A10 for PG&E). For the most part, these were customer accounts with maximum demands in the range of 200 to 500 kW. Two things should be noted about the price signals that these RTEM customers received prior to and after being converted to TOU pricing. First, even though they previously faced seasonally flat *energy* prices, they also faced seasonal demand charges. These have the effect of giving customers *implicit* price signals that electricity is more costly during summer periods in which they are most likely to set a new maximum demand level, such as during their own peak usage hours. Second, the new TOU energy prices, which are described in detail in Sections 5 and 6, consisted of peak and off-peak prices that did not differ greatly.

Quantitative Evaluation Issues

The objective of the quantitative evaluation was to measure changes in consumer load patterns that can be attributed to either or both the switch to TOU pricing, for those smaller customers who faced new TOU energy prices, and the immediate access to information on their usage patterns. However, achieving this objective was limited by a number of technical challenges. The fundamental challenge was the lack of an experimental design, including a "control" situation to serve as the comparison point for consumers' usage after receiving the RTEM equipment. That is, a typical quantitative evaluation of a public policy program or action involves a control group situation, represented by, for example, conditions prior to implementing the program, or a control group of customers that are not subjected to the program. Control situations in the case of the RTEM program were very limited, as indicated by the following features:

- All eligible customers were provided with RTEM equipment, leaving no contemporaneous control group of non-participating customers.

- All large customer accounts of size > 500 kW already faced TOU energy prices and were not changed to a new rate.
- All smaller customer accounts were switched to a TOU energy rate, again leaving no contemporaneous control group of similar customers remaining on flat rates.
- For the smaller customer accounts that were switched to a TOU rate, no TOU energy consumption data existed prior to their receiving the RTEM meters and being switched to TOU pricing.
- Even in the absence of TOU energy prices, PG&E and SCE customers faced summer demand charges that gave customers an effective price signal during periods of their highest loads that their bill would increase if they set a new maximum demand. Furthermore, the Peak/Off-peak price ratio for the new TOU energy prices was relatively low (*e.g.*, approximately $0.15/kWh to $0.08/kWh for PG&E). As a result, the incremental TOU price signal sent by the new TOU rate was relatively weak.
- Finally, even in cases where consumption data were available for time periods prior to installation of the RTEM equipment (*e.g.*, load data for PG&E's E-19 customers, who were metered and faced TOU energy prices prior to RTEM), the prior period was represented by 2000 and/or 2001. These were periods in the midst of and shortly after the California energy crisis, in which consumers were strongly encouraged to reduce consumption, especially during summer peak periods, regardless of the price.

As a result of this lack of traditional control period or group, we were forced to turn to other methods of defining a "change" situation in which consumers' usage in one period could be compared to another to draw inferences about the effect of RTEM and the new TOU rates. For example, SCE's summer TOU rates apply in the months of June through September. Therefore, we compared consumers' usage during the summer peak period to usage during the same period in the non-summer months (after controlling for weather differences) to see if we could find evidence of peak-period load reductions in the summer months relative to the non-summer months. For most customers, it was difficult to detect significant weather-adjusted load changes between summer and non-summer months. However, at least some customers did show apparent evidence of load shifting away from summer peak periods.

QUALITATIVE EVALUATION

Information for the qualitative evaluation was obtained through telephone interviews with utility project managers and customer account executives. Research topics included customer perception of the meter installation process, the information package provided by their utility, the instructions for accessing their data on the website, customers' use of their energy usage information, and any load-change actions they report having taken.

Interviews with Utility Project Managers

Christensen Associates conducted telephone interviews with the RTEM program managers at each of the utility organizations that have participated in the RTEM program. These include the three major privately-owned utilities, the two large municipal utilities (LADWP and SMUD), and SCPPA and NCPA. The interviews were conducted using an open-ended discussion guide that was designed to allow the respondents to tell their story about their participation in the RTEM program. The primary purpose of these interviews was to identify "lessons learned" by program administrators.

Our interviews with the utility project managers produced information on their views on the RTEM project overall objectives, their perspective on customers' reactions to the meters and the access to usage data via website, and any roadblocks they experienced in implementing the project.

Perceived Program Motivation and Goals

At the beginning of the interviews, we asked respondents for their perception of the primary reasons for undertaking the RTEM project. Nearly all identified difficulties in the California power markets during 2000/2001 as the driving factor behind the establishment of the RTEM program. Many of the respondents mentioned their experience with earlier efforts of the CEC to implement demand response programs for large commercial and industrial customers. Those mentioning this earlier effort tended to believe that the previous effort helped them in accomplishing the RTEM project. The previous CEC program allowed utilities to develop expertise in understanding and implementing advanced metering programs and some of this knowledge proved useful in implementing the RTEM program. Items that were typically mentioned included familiarity with metering and communications technologies, and familiarity with potential vendors.

Respondents typically fell into two groups when discussing perceived project goals. The first group tended to define the project goals in terms of accomplishing the specified number of interval meter installations and fulfilling the terms of the contract with CEC. All respondents felt that the program either had, or soon would, accomplish the narrowly defined goal of achieving the specified number of installed interval meters.

A second group of respondents tended to define the project goals in terms of enhancing customers' ability to optimize their electricity use. Several respondents offered examples of what they consider program benefits beyond mere meter installation. Examples included the following:

- *Resolution of bill disputes*: The detailed data provided by the meters allowed utility representatives to better explain customer bills.
- *Identification of energy efficiency opportunities*: Utility representatives and/or customers can use the detailed meter data to identify energy efficiency opportunities.
- *Reduction of Bills*: Some customers may be able to use the detailed meter data to identify ways in which they can modify operations to reduce impacts of demand charges. Typically these opportunities were associated with modifications of a customer's operation to reduce demand charges.
- *Compare and explain relative energy costs across similar facilities*: Some customers had several meters installed. Some of these customers indicated that they were now able to better compare energy use across facilities.

Reported Customer Uses of Metered Data

Most respondents were only able to provide limited specific examples of customers taking advantage of the capabilities of the websites and access to their usage data. In some cases, respondents were aware of specific actions undertaken by the customers, but in most cases they indicated that they had only second-hand knowledge of customers' use of the usage data. Specific examples reported by respondents included the following:

- One respondent indicated that he/she knew specifically of five customers that had made significant changes in energy use because of the access to their usage data.
- One respondent indicated that "feedback from the customer indicates that they have made changes."
- Another respondent indicated that feedback from customers was positive. This respondent said anecdotal evidence indicated that one customer had used the usage data to help prepare an end-of-year energy budget, and had been able to preserve several jobs as a result. Another customer reported using the energy usage data to develop a company energy policy.

One indicator of the potential value of the data comes from comments by several respondents that some customers requested that all of their current meters be replaced with interval meters. One respondent noted that one customer with multiple facilities liked the information provided through the program so much that they indicated a desire to have all of their meters enrolled in the program. In general, these requests could not be accommodated since the other accounts did not meet the program requirements of a minimum 200 kW demand. However, the existence of these requests provides evidence that at least some customers are finding the data sufficiently useful to believe it would be valuable to have this information for all their accounts.

One respondent reported seeing a significant increase in traffic on its website during a Stage Two Energy Emergency. This was taken as a possible sign that customers were looking at their data to help change their energy use during an emergency period. Another respondent indicated that a measure of success for his company was that they wanted to implement the program without having any customers contact the Public Utilities Commission with a complaint or concern about the program—a goal that was very nearly accomplished to the best of the respondent's knowledge. The program did, however, generate three calls to the utility with concerns about mandatory changes to TOU rates that accompanied the new meters.

While the respondents were able to cite some specific examples of how customers were using the data collected by the interval meters, most respondents indicated that it appears that many customers do not actually use the website to obtain usage data. Other comments reflected some doubts about customers' use of the interval data, or occasional technical problems in implementing the website. Regarding the number of customers retrieving data from the website, one respondent noted, "It just seems to be a product adoption process. People have lots of other things to think about." This respondent also mentioned that at some times the system seemed to "lock-up" due to some possible problem at the utility end of the communication process. The respondent reported that this issue has been addressed by increasing the frequency with which the communications process was monitored. This allowed problems to be quickly detected and resolved.

Several respondents identified the issue of non-local corporate decision making as a possible barrier to the effective use of usage data by customers. That is, if energy decisions for a large number of facilities (perhaps scattered around the country) are made in a central corporate office, then the decision-maker might have less interest in basing those decisions on usage data (however detailed) for one facility. On the other hand, at least one respondent noted that the ability to access the data from anywhere in the country was appealing to at least one of their customers. “It was great that people in Atlanta could look up the data for their facility in XXXXX.”

Program Roadblocks Encountered

Respondents reported various difficulties experienced in implementing the RTEM program. One barrier involved difficulties associated with use of telephone lines as the primary means of communications. These difficulties, when mentioned, were typically related to installation difficulties, including the following examples:

- awkward locations of existing telephone lines relative to the meter location,
- difficulties in coordinating meter installation and phone line installation
- difficulties in activating phone lines
- a long time frame required for installation of phone lines.

A few respondents mentioned minor problems with customers that were reluctant to allow physical access for the meter installation. These customers were either suspicious about being moved to a new rate, had worries about possible interruption of service, or had concern about security issues.

Another, and perhaps more subtle, roadblock involved the changing nature of the electricity market in California. One respondent noted that the program was established during a period of “crisis” and that now this crisis had passed. The lack of a sense of crisis may reduce the desire of some customers to closely manage their electricity use. In addition, one respondent noted that the slowing economy has tended to reduce the revenues of some utilities. As a result, the incentives for utilities to aggressively promote the energy and demand savings potential that might be realized by participants with accounts enrolled in the RTEM program may not be as strong as in previous years.

In a similar vein, at least one respondent indicated that customers were currently less worried about high electric bills than they were about high natural gas bills. The implication of this comment was that the lessened sense of “crisis” in the electricity market reduced the value of information about usage to the respondents.

Finally, several respondents mentioned the lack of real-time-prices as an impediment to accomplishing the RTEM project goals in the broadest sense. Even so, these respondents indicated that the installation of the metering and communications technology represented a significant infrastructure investment that would be available to support RTP in the future. While not a direct roadblock, the lack of wide spread real-time prices was mentioned by several respondents as a factor that tended to reduce the benefits that might be obtained from the RTEM program. Respondents mentioning this issue tended to believe that while TOU rates provided some economic incentive to change electricity usage patterns, the presence of real-time prices would greatly enhance incentives to modify energy usage patterns.

Interviews with Customer Account Executives

We also conducted interviews with several key account representatives at three of the utilities. The purpose of these interviews was to obtain a perspective on RTEM customer reactions to the program—in particular how customers were reacting to access to electricity usage data collected by the interval meters. Names of customer representatives were provided by relevant RTEM project managers.

In general, the interviews with customer account executives confirmed what was heard during the project manager interviews. Many customers receiving meters appear to be relatively indifferent to the RTEM program. This indifference could be explained in terms of two factors: Either customers don't perceive significant benefits from intensively monitoring their energy usage, or they aren't aware of how the usage data might be used to reduce their electricity costs. If the latter is the primary factor, it suggests that additional efforts aimed at educating customers about how they might benefit from the usage data would enhance the program benefits. As an example, one account representative prepared usage reports based on data collected as part of the RTEM program and then reviewed these reports with customers. One customer indicated that his/her operation was automatically controlled by an energy management system that shut off equipment as needed. The data from the interval meter suggested that the energy management system perhaps was not functioning in the manner in which the customer thought it was because the interval meter showed some substantial loads in the very early morning hours. In the words of the account representative, the review of actual usage data was "a real eye-opener for some of the customers."

When asked about customer usage of the website, the account executives indicated that to the best of their knowledge most customers did not visit the website to collect and analyze usage data. For the smaller number of customers who the account executives believe do access the data, they indicated that intensity of use of the website varied across customers. Some customers visited frequently (for example, daily or weekly), while others only viewed their usage data on a less frequent basis. The account executives were able to identify specific instances in which RTEM customers were able to use load data to reduce demand charges and to tie energy usage patterns to specific processes or equipment use.

The account executives reported that customers viewing their usage data generally expressed satisfaction with the RTEM program. One account representative cited a specific RTEM customer that liked the easy access provided to their energy usage data. After completion of the RTEM program, this customer added another facility and asked if they could pay to have an interval meter installed on the new facility.

The customers using the website apparently used their energy usage data in a number of ways. As might be expected, the account executives mentioned some specific examples of customers using the data to actively manage their energy use. For example, one account representative reported that a school district looked at usage data to identify load associated with air conditioning, and then evaluated the possible merits of adjusting the cooling program to reduce energy use.

Interestingly, some uses of the RTEM data may not be motivated solely by a desire to reduce energy bills. For example, the use of the RTEM data to settle billing disputes was mentioned by one account executive. Likewise, another account representative mentioned that a manufacturer used the load data to tie levels of electricity usage to specific time periods in which particular "rush" orders were being prepared. Another manufacturer was able to able to identify a facility that had low loads during periods when the load was expected to be high. The discrepancy between actual use and expected use allowed the manufacturer to identify a possible problem with employees at a specific facility.

The only negative customer reaction to the RTEM project involved the switch to TOU rates. One customer representative reported that a few customers expressed concerns that the mandatory switch to a TOU rate that accompanied the meter would result in a higher electricity bill.

Lessons Learned

Many aspects of the RTEM program were unique due to the extremely tight timeline imposed by the crisis atmosphere that produced the program in the first place. However, some general conclusions regarding lessons learned may be drawn from the respondents' comments. First, close attention should be paid to the testing of the interface between the meters, the communications system, and the utility data management system to avoid difficulties during rollout.

Second, the apparent concerns on the part of at least some customers about being transferred to a TOU rate suggest an area of concern if a similar type of metering project were to be undertaken for groups of smaller customers. Mandatory assignment to TOU tariffs would likely cause bill increases for some customers unless modifications to the rate design were made to insure some degree of revenue neutrality at each customer's pre-participation pattern of electricity usage.

Relatively little information was obtained from the RTEM program managers about customer use of the websites to obtain information about their energy usage patterns, or what actions they may have taken as a result of having access to this data. Some information of this type was developed in subsequent interviews with a few customer account representatives. Additional information was obtained from SCE and PG&E on actual customer use of the websites, as described in the following sections.

ANALYSIS OF SDG&E BILLING DATA

San Diego Gas and Electric was the first utility to respond to a request for data on their customers who received new equipment under AB29X. They provided monthly billing data and hourly interval load data for the period 1999 through 2002 for all customer accounts of size > 300 kW, for the period in which such data were available. For some larger customer accounts, such as those > 500 kW, load data were provided for the entire period. For smaller customers, data were provided for the period only after the metering equipment was installed, which generally began sometime between fall 2001 and spring 2002.

We conducted an initial analysis of the billing data of the subset of customers for whom TOU usage data were available for all four years. The analysis was designed to explore changes in patterns of overall electricity use and usage by TOU period over the period that extended from before, to during and after the energy crisis in 2000/2001. SDG&E customers experienced a number of price changes over that period, as well as exposure to all of the news regarding the crisis and to any rolling blackouts that occurred.

Analysis of Billing Data

The analysis of billing data proceeded in the following steps:

- For each customer in each year, we aggregated data across months to produce summary measures of Total kWh, Summer kWh, Summer peak period kWh, and Summer maximum demand;
- We then calculated changes in those values between the years 1999 and 2001, to examine possible effects of the crisis period and the rate increases experienced, and 2001 to 2002, to examine any additional changes that may have occurred after installation of the RTEM equipment;
- Finally, we combined the customer accounts into categories based on SIC codes, and aggregated the usage and usage changes to the group level.

Figures 4.1 through 4.3 illustrate the patterns of usage changes for three business types. The overall results, which are similar for each type, may be summarized as follows:

- Eighty to ninety-five percent of customers reduced peak energy usage between 1999 and 2001
- Of those, the typical reduction in peak kWh, summer kWh and peak demand was 10 to 20 percent
- In contrast, between 2001 and 2002, only 10 to 50 percent of customers reduced peak energy usage
- Of those, the typical reduction in the three measures of energy use was less than 10 to 15 percent.

Figure 4.1 Changes in Peak Energy and Demand: 1999-2001 and 2001-2002 (*miscellaneous manufacturing*)

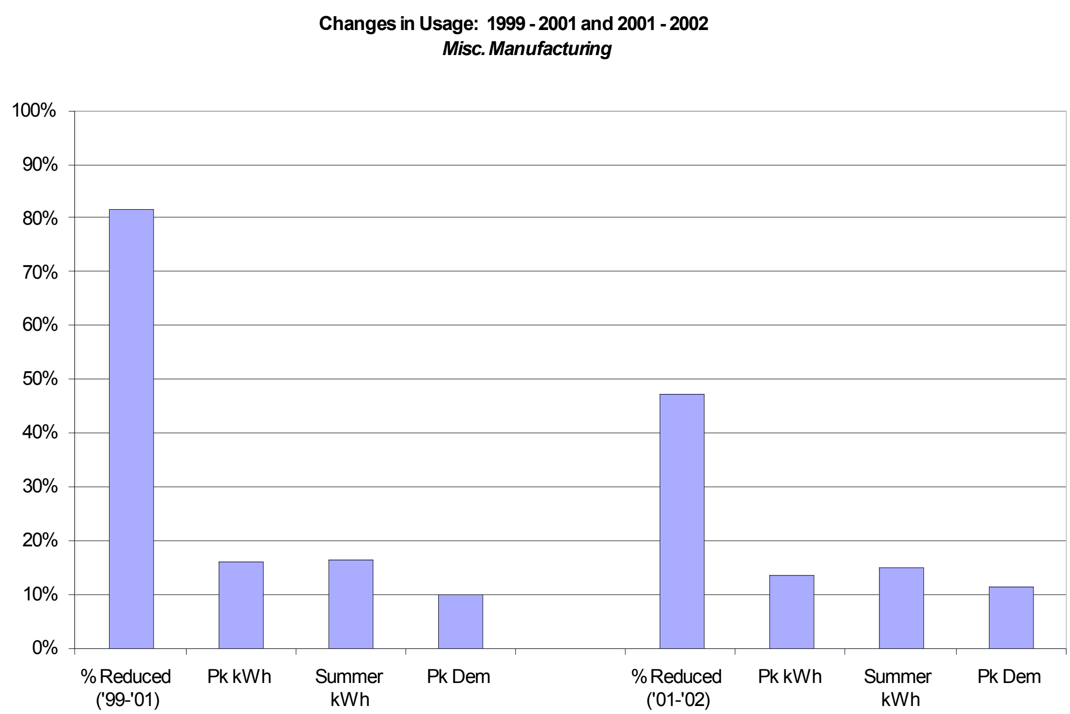


Figure 4.2 Changes in Peak Energy and Demand: 1999-2001 and 2001-2002 (*retail department stores*)

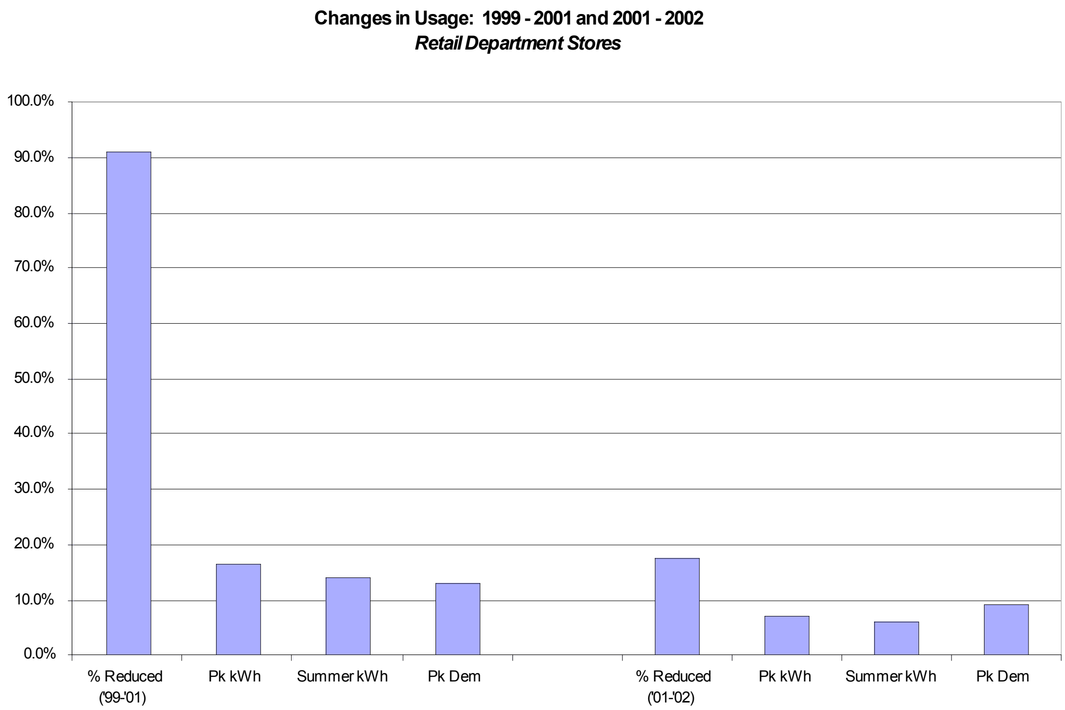
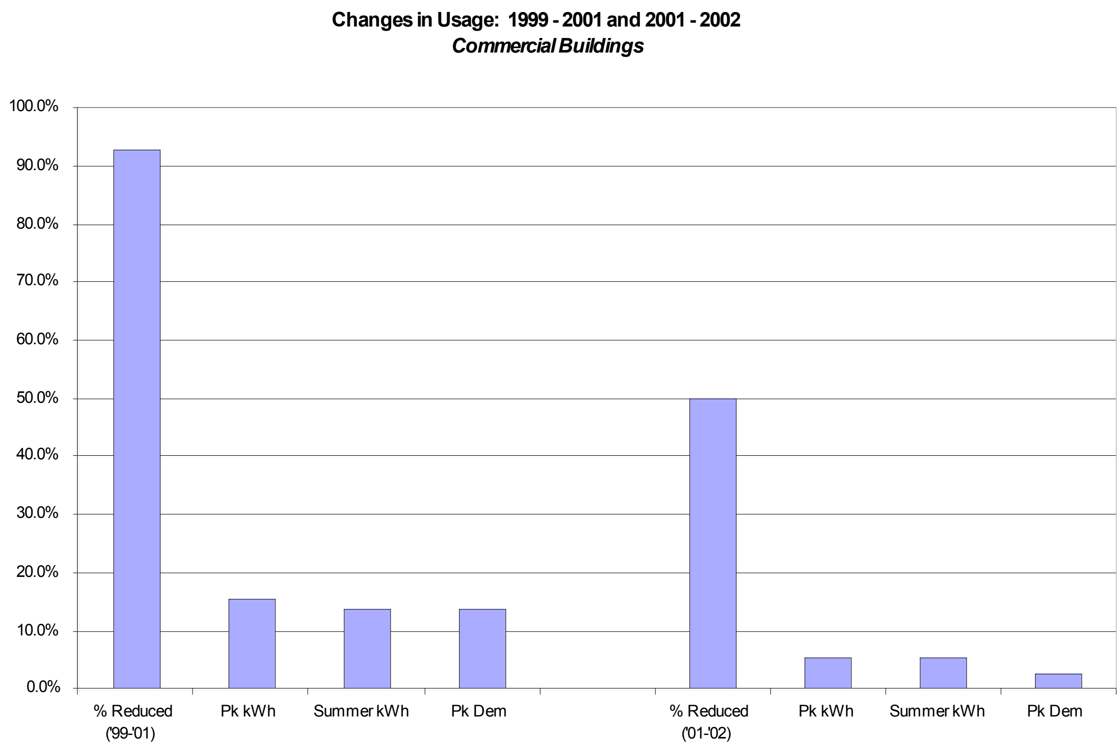


Figure 4.3 Changes in Peak Energy and Demand: 1999-2001 and 2001-2002 (*commercial buildings*)



ANALYSIS OF SCE LOAD DATA

Introduction

Southern California Edison (SCE) set up a set of website tools under the name EnergyManager to provide its RTEM customers with access to their interval load data through a set of web-based tools. In May 2003, SCE undertook a survey of a sample of customers that received RTEM equipment. They were interested in particular in customers' reaction to the EnergyManager website tools, including those optional features for which SCE charged extra fees. SCE agreed to make the survey data available to this CEC project, along with other related data for the survey respondents. Three types of data were provided:

- Survey responses from the sample of RTEM customers who participated in a telephone survey.
- Information on the number of times that each of the survey participants accessed the SCE EnergyManager website each month during the period from March 2002 to February 2004.
- Hourly interval load data for each of the survey participants from the time the equipment was installed until approximately October 2003.

This section of the report summarizes findings from our analysis of the integrated set of survey, website, and load data, including analysis of load changes by RTEM customers, and the extent to which those load changes may have been affected by their use of the EnergyManager information.

SCE Customer Survey

SCE conducted its survey via telephone during May and June, 2003 with approximately 300 customers who were eligible to participate and receive data through the EnergyManager (EM) system. For those customers who were actually signed up for EM, SCE asked a series of questions about the customers' use of and satisfaction with the software and website. Among the overall results, approximately 85% of the customers reported being satisfied or completely satisfied. Customers on average reported that 7.3 employees were using EnergyManager at their facility, and reported the following frequency of use:

At least once a day	15%
At least once a week, but less than daily	29%
At least once a month, but less than weekly	27%
Only for a specific need	26%
Don't know	3%.

SCE asked several questions regarding the usefulness of EnergyManager for a variety of tasks, including shifting energy consumption or peak demand away from peak periods, and reducing energy costs. Approximately 40% of the respondents reported that they had used EnergyManager to take each of the actions asked about, including the following:

Shifting energy usage away from On-peak hours
Shifting energy demand away from On-peak hours
Reducing overall energy usage
Reducing energy demand.

In addition, about 50% of the respondents reported “reducing costs,” and 30% reported installing energy efficiency equipment as a result of using EnergyManager.

Results for GS2T and TOU-8 Customers

The two largest groups of customers included in the survey were those taking service under two retail tariffs—GS2T (for customer accounts with maximum demand between 200 and 500 kW) and TOU-8 (for customer accounts in excess of 500 kW). These two groups were the focus of our analysis. Table 5.1 provides survey results on certain key questions for subsets of the two rate groups defined by business type—*industrial* (SIC codes 20 through 49) and *commercial* (SIC codes 50–89).

Table 5.1 Summary of SCE Survey Results

GS2T							Frequency of use					
EM users	Obs.	Shifted Peak kWh	Shifted peak kW	Reduced overall kWh	Reduced maximum kW	Ave. # of Users	Daily	Weekly	Monthly	Specific need	% with Web hits	Avg. Web hits / obs.
Industrial	27	41%	33%	33%	41%	1.5	11%	37%	15%	37%	81%	44
Commercial	27	33%	48%	37%	37%	4.1	15%	22%	30%	22%	74%	23
Non-users												
Industrial											28%	2
Commercial											24%	23

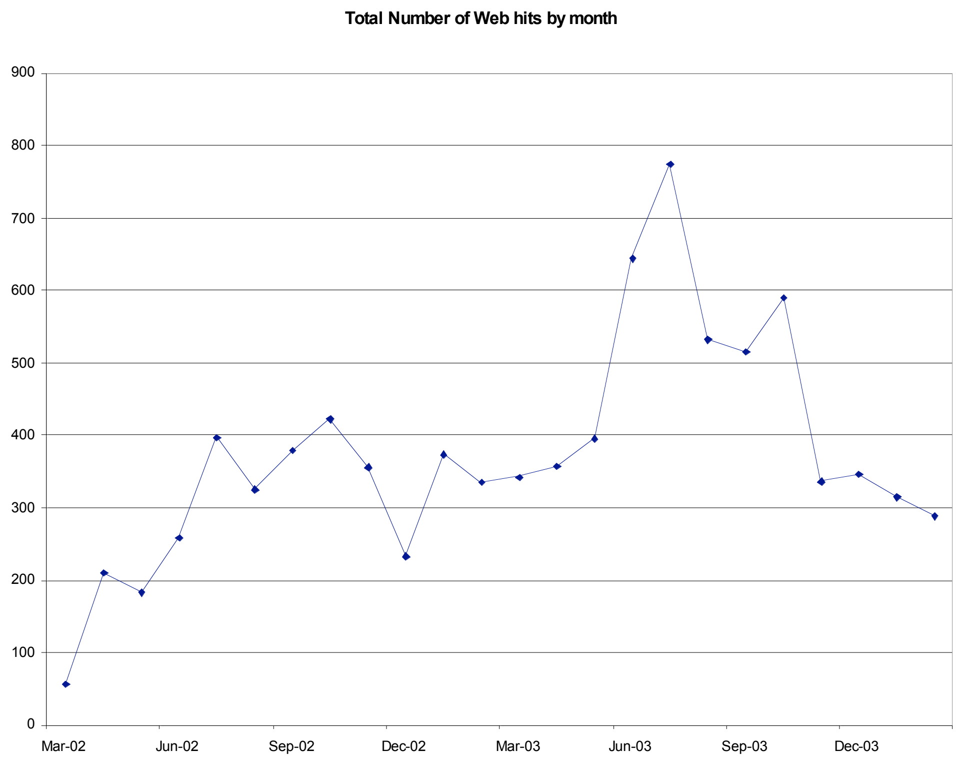
TOU-8							Frequency of use					
EM users	Obs.	Shifted Peak kWh	Shifted peak kW	Reduced overall kWh	Reduced maximum kW	Ave. # of Users	Daily	Weekly	Monthly	Specific need	% with Web hits	Avg. Web hits / obs.
Industrial	25	44%	40%	52%	44%	6.2	16%	24%	44%	16%	80%	44
Commercial	22	36%	32%	50%	55%	1.9	23%	41%	9%	27%	95%	96
Non-users												
Industrial											65%	5
Commercial											79%	107

The results suggest some minor differences in respondents’ indications of their use of the EM tools for various cost-saving changes in energy use. For example, GS2T industrial customers reported somewhat more use for shifting peak period energy usage and reducing maximum demand. However, in other cases the commercial users reported greater use for shifting or reducing peak demand. The commercial customers reported somewhat more frequent use of the EM tools, which was confirmed in the independent data on actual reported “web hits,” which is shown in the last two columns. In particular, the TOU-8 commercial customer group had the greatest percent of customers with any web hits, and the highest number of web hits per customer.

Information on web hits for the survey respondents who reported that they were not EM users at the time of the survey indicate that a substantial percentage actually have used the website over the period in which web hits data were provided. This may indicate that the survey respondents were not aware of the website use by others at their organization, or that the customer began using the website after the survey was taken.

The monthly pattern of total web hits by all of the customers in the survey sample is provided in Figure 5.1 for the period March 2002 to March 2004. The values show a definite up-tick in website usage during the summer months and somewhat of an upward trend over the two-year period.

Figure 5.1 Total Number of Website Accesses (Web Hits) By Month



Analysis of Load Changes

As discussed in the introductory section to this report, the nature of the RTEM project did not lend itself to classical impact evaluation methods through the use of control groups or control periods for purposes of comparison to program participants. For example, in the case of the SCE data, load data were provided for all customer accounts only for the period *after* the RTEM equipment was installed. At that time, the GS2T customers were switched from the GS2 tariff, which had seasonal demand charges and flat seasonal energy prices, to the companion GS2T tariff, which had the same demand charges but new seasonal TOU energy prices.

Thus, during the period for which load data were available, all customers in a given rate class faced the same TOU energy prices throughout the entire period. In addition, while the survey data provide information on customers' reported use of the EM tools, they provide no indication of when those actions might have started, and thus no way to include an impact variable in the analysis to indicate a date as of when some action might be expected. The only such data available are the web hits data, which we attempted to incorporate in the analysis.

TOU Prices

The tariff prices faced by the two rate classes are shown in Table 5.2. For purposes of understanding the price incentives inherent in utility tariffs that contain both demand and energy charges, we find it useful to combine the charges into a single measure of customers' *effective energy charge* (EEC) during particular time periods. The EEC in a given hour, or time period, indicates the change in a customer's monthly bill for a unit change in consumption in that time period.

The EEC effectively allocates demand charges over hours in a month in proportion to the likelihood of incurring an additional demand charge in those hours. For example, if a peak demand charge applies in 126 hours of a month (6 hours on each of 21 weekdays), and a customer perceives that it is equally likely of setting a new billing demand in any of those hours, then the demand charge may be allocated equally across all of those hours (*e.g.*, for the TOU-8 tariff, the $17.95/kW demand charge would be allocated by a charge of $.14/kWh to each peak period hour). The allocated demand charge may then be combined with the energy charge to produce an estimate of the customer's effective cost per kWh in each peak hour.[7] Figures 5.2a and b illustrate EECs for the GS2 (with and without the TOU energy prices) and TOU-8 tariffs respectively, for the summer and non-summer months. Note in particular that the EEC during the peak period defined by the summer prices is much higher during the summer than non-summer months for both tariffs, while the change to TOU energy prices had only a modest effect on GS2T customers' summer peak EEC.

Table 5.2 SCE Tariffs
(Summer = June – September)

	GS2		GS2T		TOU-8	
	Summer	Winter	Summer	Winter	Summer	Winter
Demand charges ($/kW)						
All hours	$ 5.40	$ 5.40	$ 5.40	$ 5.40	$ 6.60	$ 6.60
Seasonal	$ 7.75		$ 7.75			
On-peak					$ 17.95	
Mid-peak					$ 2.70	
Non-TOU energy charges ($/kWh)						
First 300 kWh/kw of Max demand	$ 0.119					
Additional kWh	$ 0.135					
TOU energy charges ($/kWh)						
On-peak (Hrs 13 - 18)			$ 0.179	$ -	$ 0.132	
Mid-peak			$ 0.122	$ 0.130	$ 0.054	$ 0.065
Off-peak			$ 0.106	$ 0.106	$ 0.035	$ 0.036

7

Figure 5.2a GS2T Effective Energy Charges (before and after change to TOU energy prices)

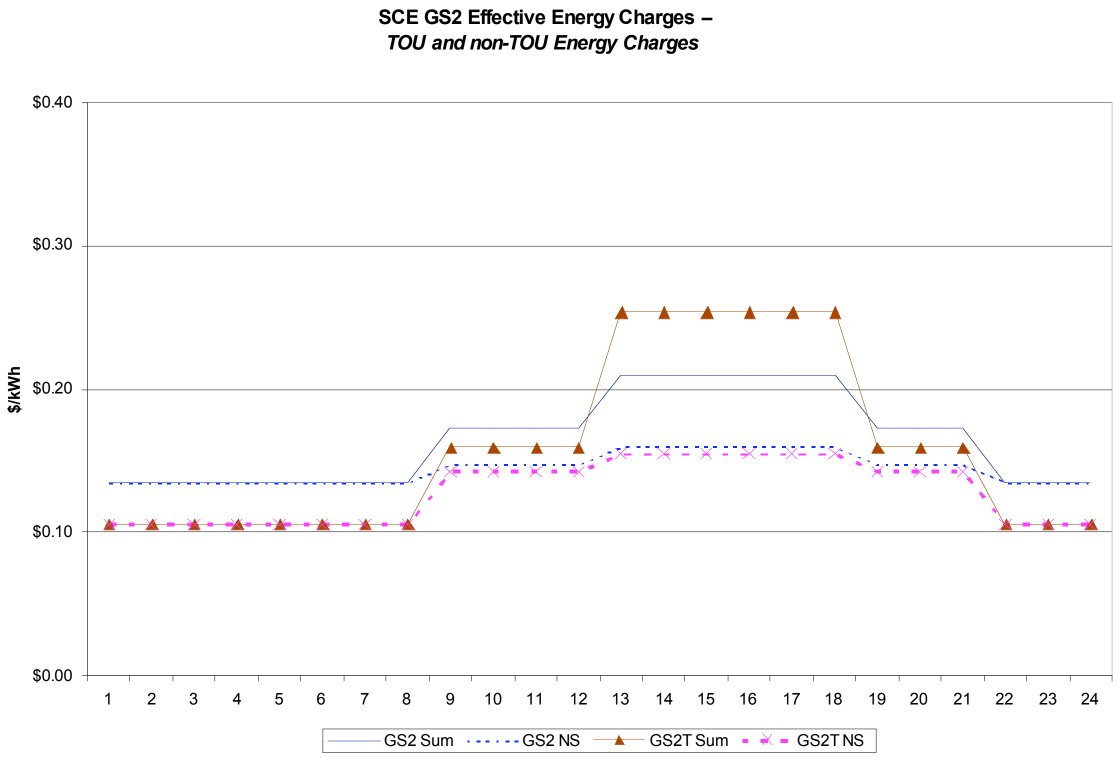
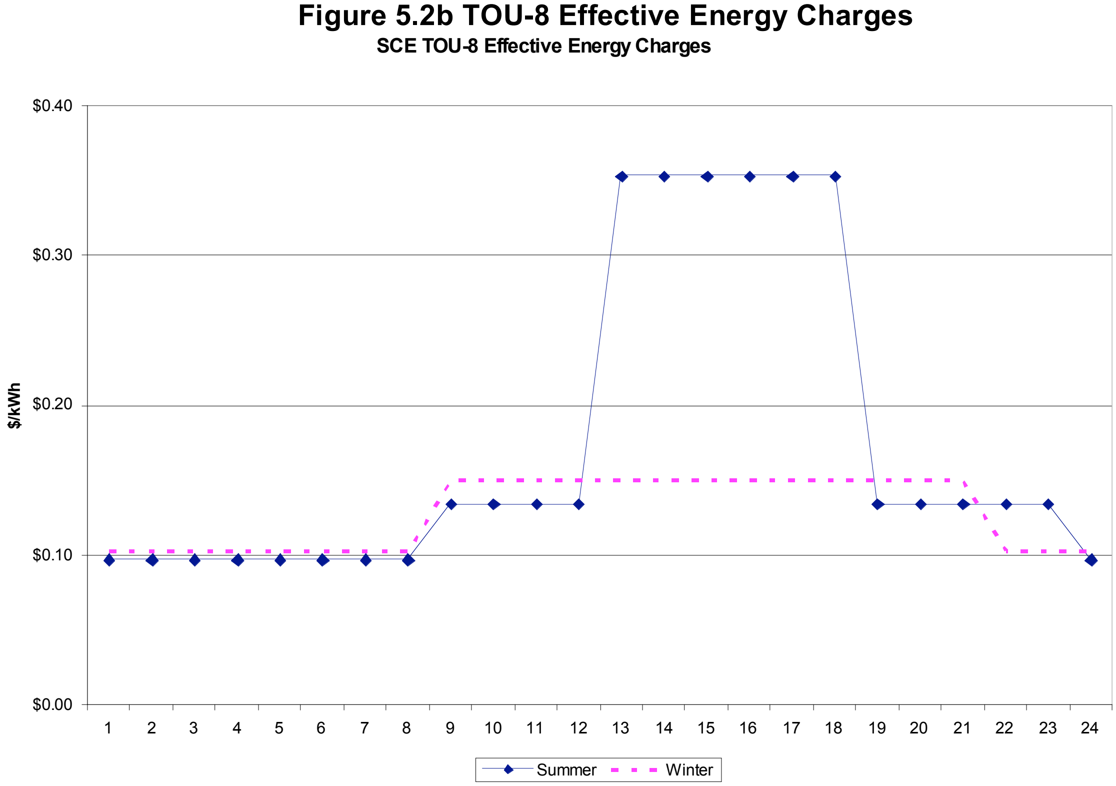


Figure 5.2b TOU-8 Effective Energy Charges



Several important observations may be made about the prices faced by the GS2T and TOU-8 customers, both before and after they received RTEM equipment:

- Both groups faced substantial price signals that electricity was more costly during the summer (GS2T) and/or summer peak periods (TOU-8). Even though the GS2T customers did not face explicit TOU energy prices while on the previous GS2 rate, to the extent that their typical usage pattern was greatest during the afternoon hours, the seasonal demand charge implied that their effective cost of electricity was higher during the peak hours compared to the other hours of the day. This is the case because any increase in hourly usage during that period has some chance of setting a higher billing demand and thus incurring an additional demand charge.
- The new TOU energy charges under GS2T produced a relatively modest summer peak/off-peak differential of less than 2 to 1, with a peak/mid-peak differential of about 3 to 2, and a ratio of the new peak energy price to the tail-block price of the previous GS2 rate of less than that. These values suggest a relatively modest change in the effective price of electricity in the different TOU periods, as well as a relatively modest summer/winter price differential.
- In contrast, the TOU-8 on-peak price signal is very strong, with a peak/off-peak energy price ratio of nearly 4 to 1, plus a large summer peak demand charge. This price signal already existed prior to installation of the RTEM equipment.
- The only price *change* that may be observed over the time period for which customer load data were available is the effective price increase that each customer sees during the four summer months relative to the other months of the year, particularly in the peak afternoon hours. This price signal is substantially stronger for the TOU-8 customers than for the GS2T customers.

Analysis Approach

As noted above, the only price difference that can be observed for both rate classes is for the summer months of June through September, for which the demand and TOU energy prices were higher than in the non-summer months. Thus, we developed an analysis approach that was designed to measure differences in energy usage during, for example, summer peak time periods relative to the same time periods in non-summer months, after controlling for the effect of weather and other variables that might be expected to affect consumption. We interpreted significant reductions in summer peak-period usage, after controlling for other factors, as indicative of TOU price responsive behavior. We also included information on consumers' use of the EnergyManager website in the analysis to attempt to measure the effect of such use on changes in energy consumption.

We used regression analysis to implement the above analysis approach, using some variables designed to control for factors such as weather conditions that would be expected to affect daily changes in energy usage, and others designed to indicate time periods such as the summer months, and time periods during those months for which prices differed. We conducted two levels of analysis, using daily observations on electricity use by TOU time period, for the period of approximately the spring of 2002 to October 2003. The analyses included the following:

- Pooled analysis using individual customer account data within SIC groups (*e.g.*, hourly loads for all industrial-type customer accounts in SIC codes 20 – 49) for each rate class, thus resulting in estimates of parameters that average across customers in each group.

- Individual customer-level analysis, which resulted in separate estimates of price response parameters for each customer account, and an ability to examine the distribution of such parameters across customer accounts in each group.

After exploring a variety of functional forms, variables, and estimation methods, we settled on an approach of estimating separate equations for each of the following five TOU time periods (defined by hours-ending):

1. Hours 1–8 (Morning off-peak)
2. Hours 9–12 (Morning mid-peak)
3. Hours 13–18 (Peak)
4. Hours 19–22 (Evening mid-peak)
5. Hours 23–24 (Evening off-peak).

The observations in each TOU period were represented as average hourly loads during the period, for each day. Equations were estimated in both *level* and *share* form. The level equations represented average hourly usage by time period as a function of a number of explanatory variables, where our greatest interest was the equation for the Peak period. To test whether peak-period load reductions might be due to *overall* daily load changes rather than specific peak-period response to peak prices, we also estimated a single equation for *daily* electricity use, and also a set of equations in which the variable to be explained was the *share* of daily usage in each time period.

For the pooled analysis, daily observations for all customer accounts in a group were stacked, and fixed-effects estimation was performed to estimate coefficients for the group, with separate customer-specific shift coefficients included to control for systematic differences in each customer's load patterns. For the individual customer regressions, similar models were estimated for each customer, producing separate estimates of key model parameters for each customer. The specific equations used, and the empirical results obtained are shown below, following a discussion of the load data.

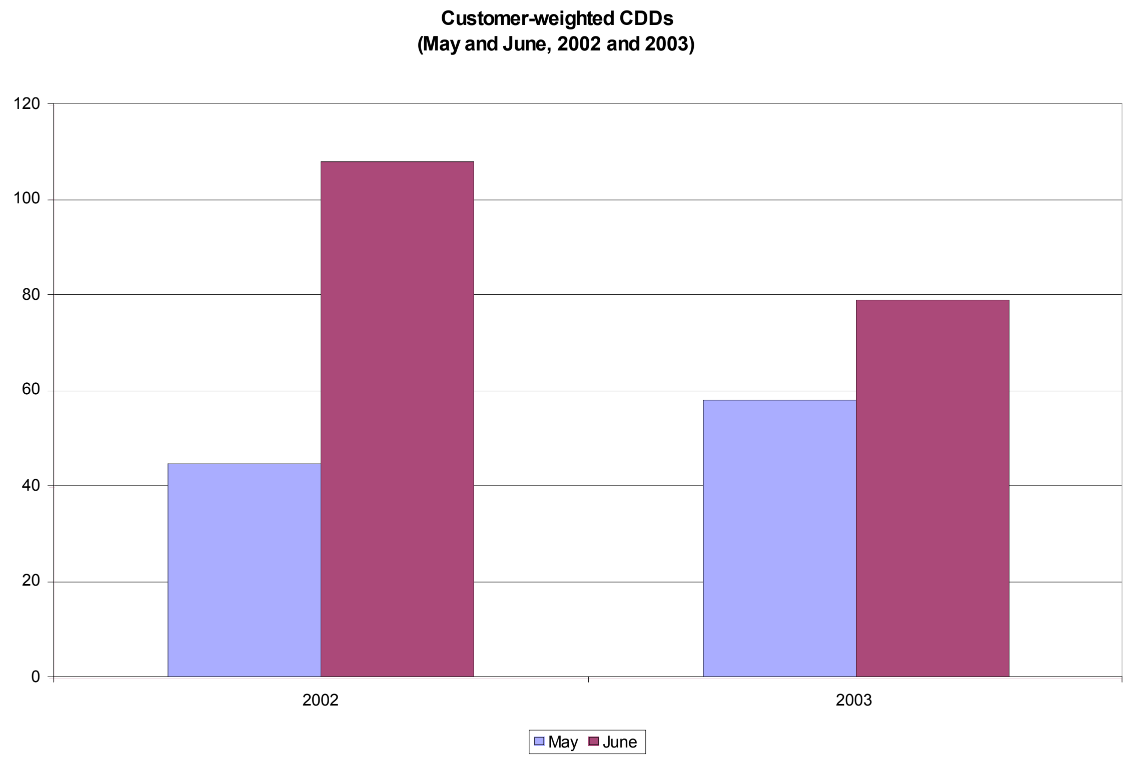
Load Data

Before presenting results of the regression analysis, we first provide a picture of the load data for several different customer groups and for different time periods. The following figures illustrate aggregate load data for several different groups of interest. The load data for individual customer accounts were first divided into groups based on *rate class* (GS2T and TOU-8), broad business type (Industrial—SIC 10–49, and Commercial—SIC 50–79), and whether the survey indicated them as an EM user (yes and no). The figures represent averages across customer accounts in each group, and then across weekdays for the following periods in 2002 and 2003:

- May, representing near summer weather conditions in the period just prior to the summer TOU pricing period, and
- June, representing weather conditions similar to May, but within the summer pricing period.

For purposes of interpreting differences in average loads between the key comparison months of May and June, Figure 5.3 illustrates the customer-weighted CDDs for those months in both years.

Figure 5.3 Weather Conditions – May and June, 2002 and 2003



Figures 5.4 through 5.7 show average May and June weekday load profiles for the indicated customer groups, for both 2002 and 2003. In each case, the loads for May are shown as dashed lines, and the loads in 2003 are shown in greyer and bolder lines than those for 2002. The following observations may be made about these figures:

- The two GS2T Industrial groups appear relatively insensitive to weather conditions. The EM-user group averages somewhat larger loads and a higher load factor than the non-EM group. Neither group shows obvious evidence of summer peak-period (hours 13–18) price response, such as a load reduction in those hours in June relative to May.
- The two GS2T Commercial groups appear more weather responsive, and have broader peak loads that fall off later in the day than the industrial loads. Neither group shows obvious evidence of price response.
- The two TOU-8 Industrial groups are relatively insensitive to weather, have high load factors, and show clear evidence of load reductions during the high-cost summer peak period. The EM-user group shows evidence of a broad "slice" of load reduction throughout the day on summer weekdays relative to May weekdays. The no-EM group shows a more pronounced load dip during the peak hours in particular, though the reduction also appears present to a lesser extent in May.
- The two TOU-8 Commercial groups show only modest weather sensitivity, and some possible evidence of peak-period load reductions in the summer months relative to May.

Figure 5.4a Average Weekday Loads – GS2T *Industrial* (EM User) (May and June, 2002 and 2003)

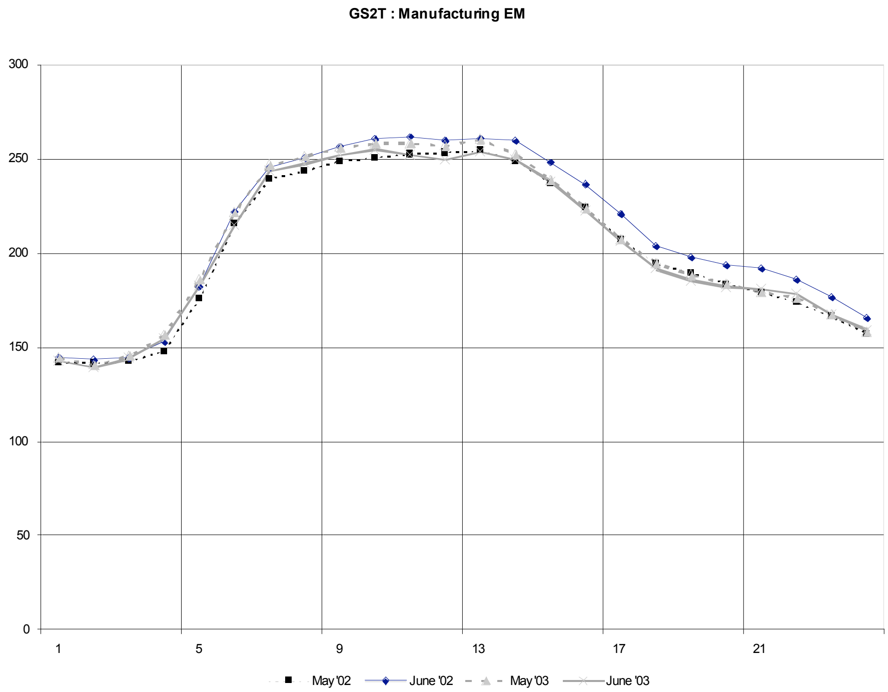


Figure 5.4b Average Weekday Loads – GS2T *Industrial* (No EM) (May and June, 2002 and 2003)

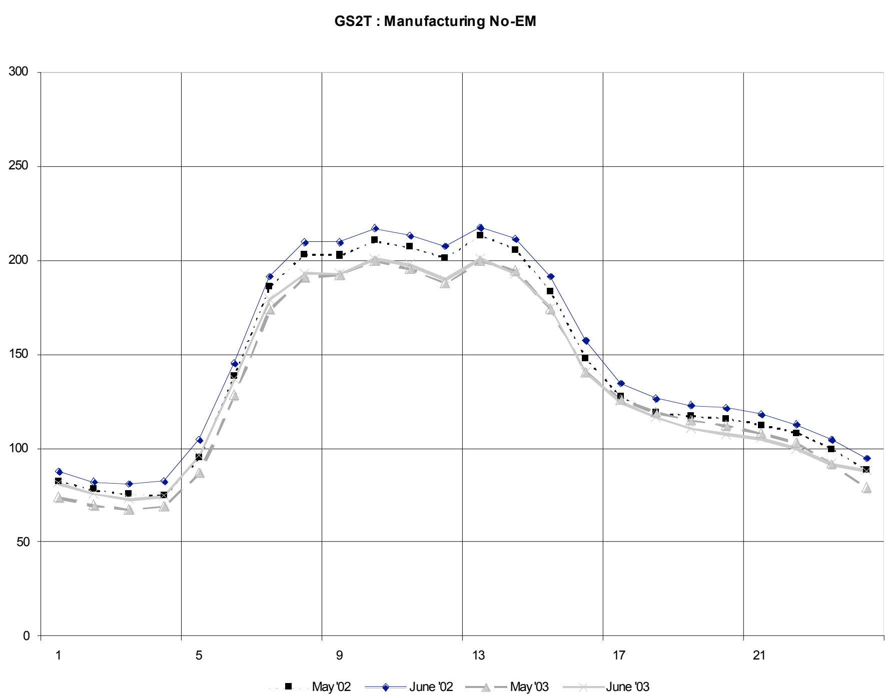


Figure 5.5a Average Weekday Loads – GS2T *Commercial* (EM User) (May and June, 2002 and 2003)

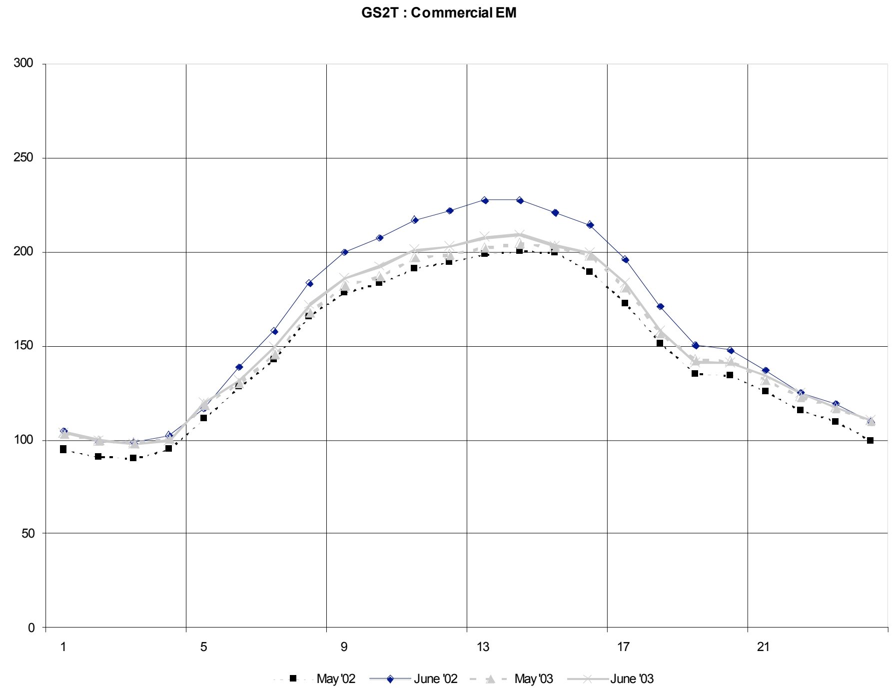


Figure 5.5b Average Weekday Loads – GS2T *Commercial* (No EM) (May and June, 2002 and 2003)

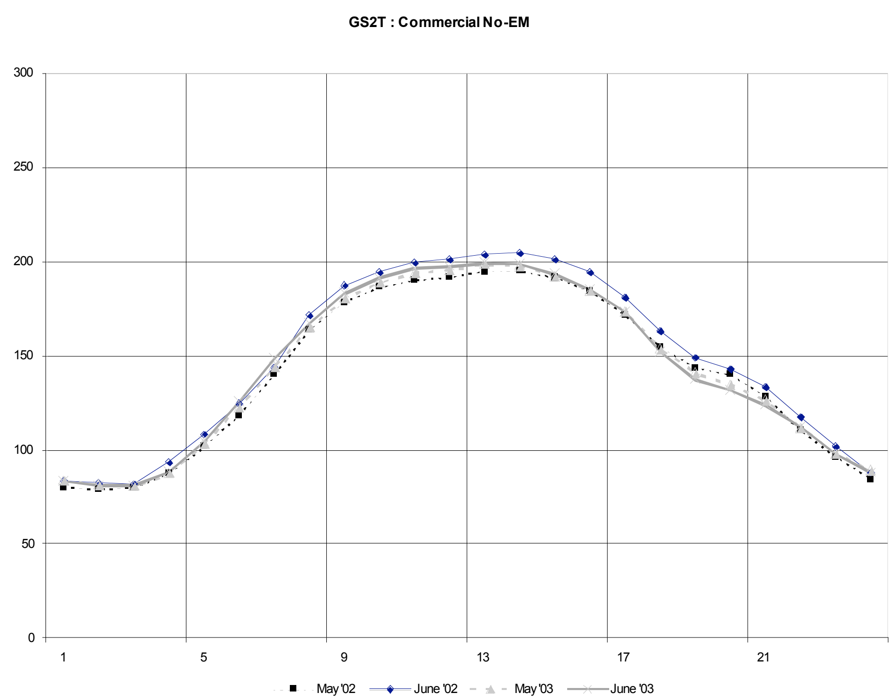


Figure 5.6a Average Weekday Loads – TOU-8 *Industrial* (EM-User) (May and June, 2002 and 2003)

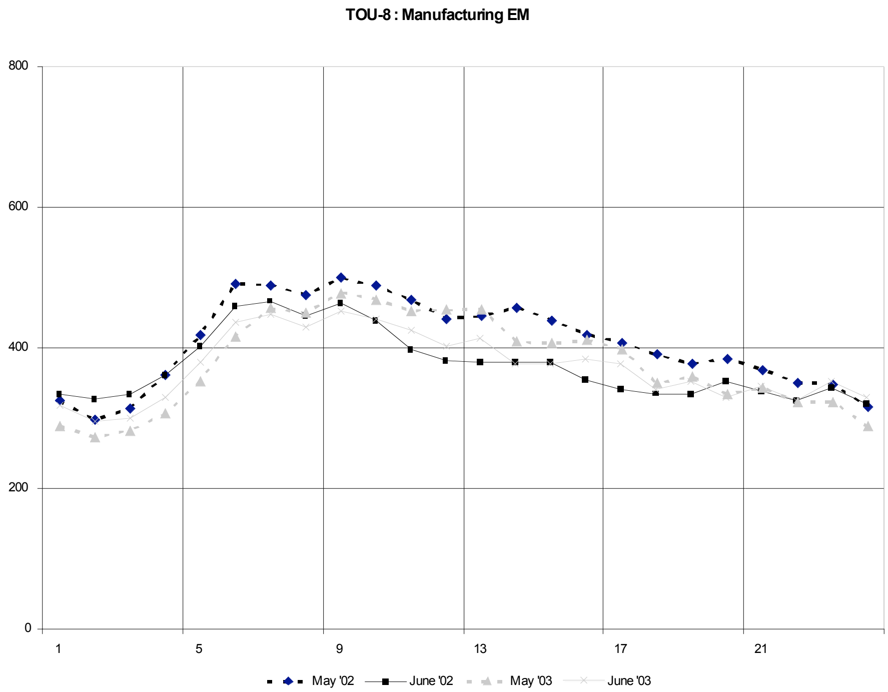


Figure 5.6b Average Weekday Loads – TOU-8 *Industrial* (No EM) (May and June, 2002 and 2003)

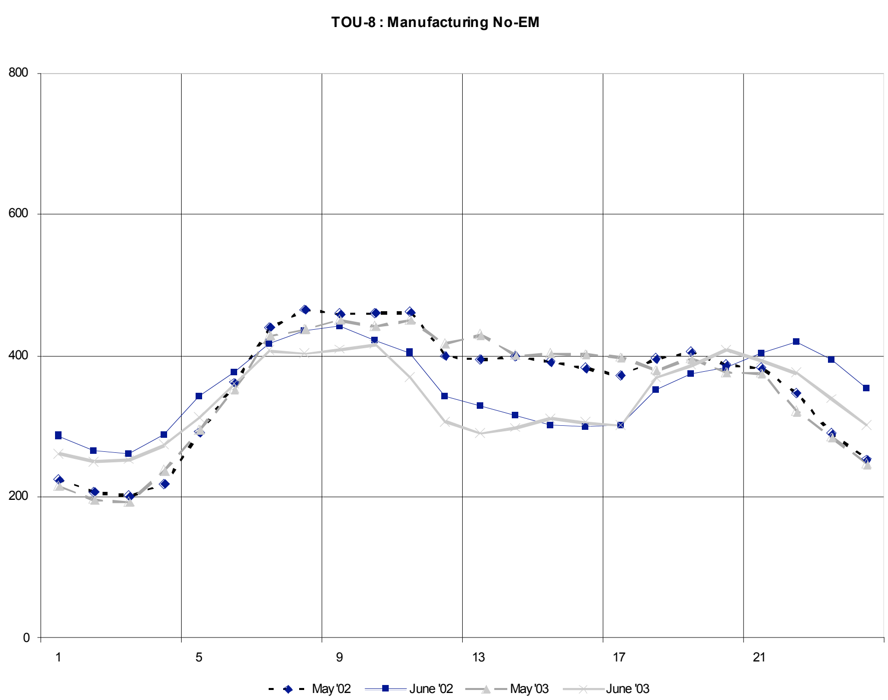


Figure 5.7a Average Weekday Loads – TOU-8 *Commercial* (EM-User) (May and June, 2002 and 2003)

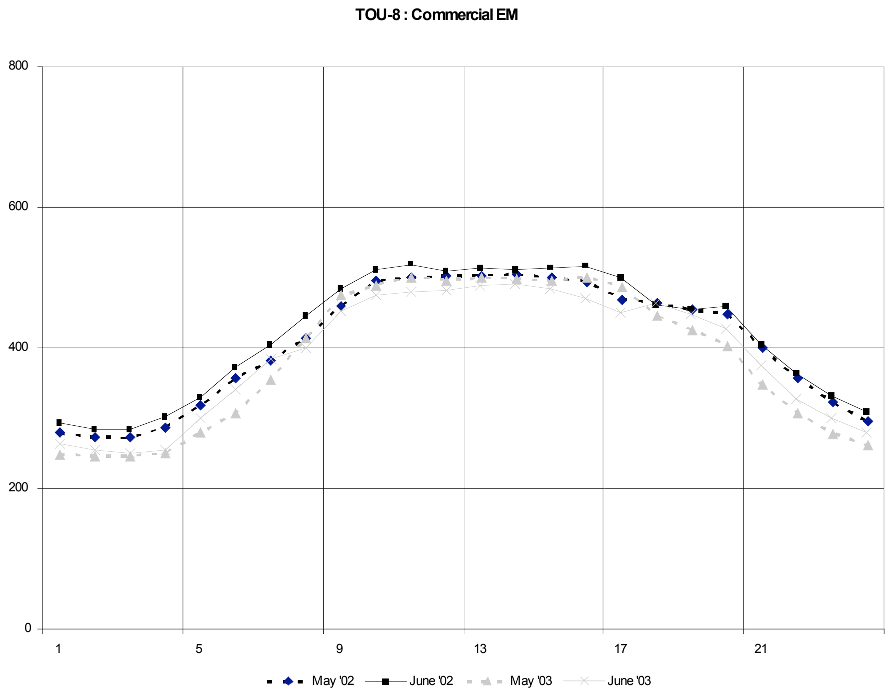
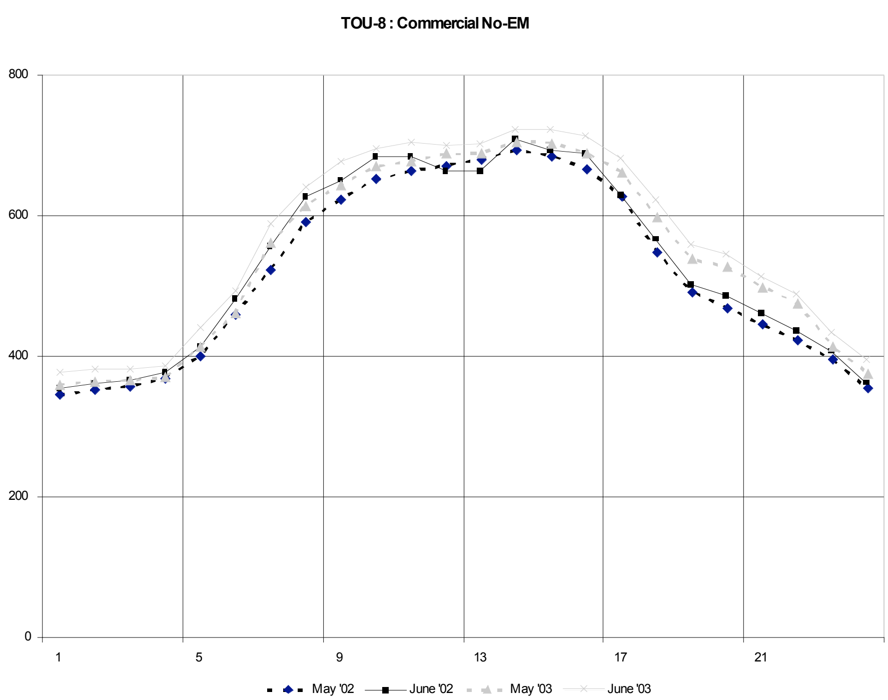


Figure 5.7b Average Weekday Loads – TOU-8 *Commercial* (No EM) (May and June, 2002 and 2003)



Econometric Analysis—Approach

The basic estimation equation may be represented as follows:

$$ln(E_{it}^{T}) = \boldsymbol{B}\,\boldsymbol{X}_{it} + d_1\ (Summer * D2002) + d_2\ D2003 + d_3\ (Summer * D2003) + v_i + e_{it},$$

where E_{it} is electricity usage for customer i on day t, T denotes five TOU periods as described above, $\boldsymbol{X}_{it}$ are variables that measure weather (quadratics of HDD and CDD), Summer is a dummy variable corresponding to SCE's Summer pricing period, D2002 is a dummy variable for the year 2002, and D2003 is a dummy variable for the year 2003. The error term is decomposed into two components: v_i and e_{it}, where v_i is unobserved customer-specific characteristics that do not change with time, and e_{it} is the traditional mean zero, normally distributed error. The customer specific component of the error, v_i, is captured in the model using customer fixed effects. All models presented below restricted analysis to non-holiday weekdays between January of 2002 and the end of October, 2003. The latter half of December and the first half of July were omitted in order to avoid seasonal effects related to the Christmas and Fourth of July holidays.

The model was used to estimate the coefficients denoted $\boldsymbol{B}$, d_1 d_2, and d_3. The natural logarithm operator is represented by *ln()*. Transforming electricity use into its natural logarithm implies that the estimated coefficients measure percentage changes. For example, a coefficient of 0.02 on CDD implies that a 10 unit increase in CDD leads to a 20 percent increase in energy usage (10 * 0.02 * 100% = 20%). For dummy, or shift variables, such as the variable for Summer 2003, the coefficient represents the shift in usage during the period <u>relative to a particular comparison period</u>. For instance, $d_3 = -0.2$, implies that energy usage fell 20 percent during the summer of 2003 relative to the rest of 2003.

By measuring relationships in percentages, changes are scaled so that relatively large or small customers do not have an undue influence on results. For example, suppose two customers are being analyzed. One customer has an average usage of 500 kW, and another has an average usage of 50 kW. If the larger customer drops usage by 100 kW during high price periods and the smaller customer drops usage by 20 kW, the average decline is (100 + 20) ÷ 2 = 60 kW. This result is unsatisfying since 60 kW is more than the smaller customer typically consumes. By expressing the changes as percentages, the estimated response to higher prices provides a more rational insight: the large customer reduces usage by 100/500*100% = 20%, while the small customer reduces usage by 20/50*100% = 40%. The average reduction using percentages is (20% + 40%) ÷ 2 = 30%.

The equation presented above was estimated for three measures of usage. The first measure analyzed was *total daily usage*. For modeling daily usage, two additional variables were included in the model: the monthly unemployment rate was used to control for changing levels of regional economic activity, and a monthly time trend was used to account for systematic but otherwise unexplained changes in the trend of usage. A second measure of usage in this analysis was *average daily usage within each of the five time periods* summarized above. Recall that the five time intervals correspond to the a.m. summer off-peak period, the a.m. shoulder period, the peak pricing period, the p.m. shoulder period, and the p.m. off-peak period. A separate regression was run for each of these five periods. The third usage measure was the *usage share* in each of the aforementioned periods. That is, for each customer on a daily basis we calculated $kWh_{it}^{T}/\Sigma_{T}kWh_{it}^{T}$, for T = 1, 2, … , 5.

Econometric Analysis—Data Screening

The number of observations and the number of customers used in the regression analysis reflected the effect of several data screens. The primary observation screens included dropping individual days where all hourly observations were zero, or where one or more hourly observations were missing. The zero observations screen affected very few days. The missing data screens affected more observations, particularly for certain customers.

Observations were also dropped in the course of merging data across sources. This affected a limited number of customers due to such problems as the inability of matching ZIP codes to weather zones for purposes of matching weather zones.

The customer-level screens were more subjective. Customers were dropped based on visual review of load profiles and summary statistics. For example, customers with only sporadic data were not retained for the analysis. Profiles that were especially idiosyncratic (such as a customer with essentially no usage in non-summer months) were also dropped. These customers' loads would be unlikely to be explained by the variables included in our analysis, and thus contribute large unexplained load variation. Finally, all accounts representing schools were omitted from the analysis due to our reliance on a method that essentially assumes that the customers' operations are similar during summer and non-summer months except for weather differences and the effect of the summer peak prices. However, schools tend to have lower loads during certain summer months due to vacation schedules.

Of the customers responding to the Energy Manager survey, 138 were GS2T customers with accounts for which load data were provided by SCE. Of these, data for 94 of the accounts were included in the econometric analysis. For the TOU-8 rate class, 67 survey respondents had load data available. Of these, 48 were included in the analysis.

Econometric Analysis—Results

The approach outlined above leads to a series of regressions that were estimated at a variety of levels, including pooled across all customers, pooled by SIC categories, and at the customer level.

Pooled estimation. Tables 5.3 through 5.6 show estimated coefficients for the GS2T and TOU-8 rate classes respectively, with separate estimates shown for the Industrial and Commercial groups. Each set of columns labeled by time period represents the results from separate regressions. The first block of estimates in each case represents those for the daily *share* equations, and the second block represents the *levels* in each time period, including a separate equation for *total daily usage*. The primary coefficients of interest are those in the Peak period (period 3) equation, especially those on the variables for summer 2002 and 2003. Statistically significant values of key coefficients are highlighted in bold. Some of the key findings in these tables are the following:

Table 5.3 Pooled Regression Results – GS2T *Industrial* (share and level equations)

Log of share used in each daily time period	Period 1		Period 2		Period 3		Period 4		Period 5			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	-0.0012	-0.83	0.0016	1.27	0.0027	2.23	-0.0062	-2.78	-0.0092	-3.75		
CDD squared	0.0002	2.02	-0.0001	-1.26	-0.0002	-3.66	0.0001	0.98	0.0002	1.79		
HDD	0.0001	0.05	0.0029	1.88	-0.0004	-0.28	-0.0077	-2.84	-0.0090	-3.02		
HDD squared	0.0002	1.34	-0.0001	-0.88	-0.0001	-0.98	0.0004	1.82	0.0005	2.36		
Year = 2003	-0.0156	-3.50	0.0114	2.97	0.0238	6.61	-0.0058	-0.86	-0.0315	-4.28		
Summer 2002	-0.0061	-0.93	-0.0067	-1.18	**-0.0102**	**-1.91**	0.0787	7.96	0.0967	8.88		
Summer 2003	0.0391	5.99	-0.0257	-4.61	**-0.0348**	**-6.63**	0.0010	0.10	0.0195	1.81		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0058	2.99	0.0088	5.16	0.0099	5.67	0.0011	0.39	-0.0019	-0.66	0.0082	5.94
CDD squared	-0.0001	-0.78	-0.0003	-3.61	-0.0005	-5.13	-0.0001	-0.85	0.0000	-0.05	-0.0003	-3.80
HDD	0.0018	0.74	0.0043	2.08	0.0011	0.50	-0.0061	-1.82	-0.0075	-2.08	0.0012	0.70
HDD squared	0.0000	0.13	-0.0002	-1.58	-0.0003	-1.59	0.0002	0.86	0.0004	1.39	-0.0001	-1.20
Year = 2003	-0.0031	-0.53	0.0248	4.82	0.0372	7.04	0.0074	0.89	-0.0184	-2.07	0.0400	5.81
Summer 2002	0.0404	4.67	0.0385	5.05	0.0346	4.44	0.1236	10.06	0.1416	10.81	0.0421	6.48
Summer 2003	0.0470	5.49	-0.0204	-2.72	**-0.0296**	**-3.84**	0.0065	0.53	0.0249	1.92	0.0135	2.11
Unemployment rate											-0.0017	-0.33
Time trend (monthly)											-0.0032	-4.96
Observations		23,002		22,999		23,000		22,999		22,999		23,002
Customers		57		57		57		57		57		57

Table 5.4 Pooled Regression Results – GS2T *Commercial* (share and level equations)

Log of share used in each daily time period	Period 1		Period 2		Period 3		Period 4		Period 5			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	-0.0052	-2.40	-0.0008	-0.94	0.0058	6.09	-0.0017	-0.76	-0.0074	-3.46		
CDD squared	-0.0001	-1.06	0.0001	2.39	-0.0001	-2.16	0.0002	1.51	0.0001	0.69		
HDD	-0.0051	-1.91	-0.0016	-1.51	-0.0023	-2.00	0.0026	0.96	-0.0057	-2.21		
HDD squared	0.0004	1.79	0.0001	1.82	-0.0001	-0.85	-0.0002	-0.79	0.0005	2.42		
Year = 2003	0.0381	5.85	-0.0047	-1.80	-0.0009	-0.32	-0.0119	-1.79	0.0491	7.71		
Summer 2002	0.0135	1.41	0.0001	0.02	**-0.0094**	**-2.26**	0.0383	3.92	0.0259	2.77		
Summer 2003	0.0342	3.57	0.0219	5.65	-0.0038	-0.93	-0.0382	-3.89	0.0010	0.11		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0081	3.51	0.0124	7.60	0.0190	9.61	0.0117	4.02	0.0064	2.50	0.0128	8.83
CDD squared	-0.0003	-1.94	0.0000	0.06	-0.0002	-2.06	0.0001	0.40	-0.0001	-0.37	-0.0001	-1.05
HDD	-0.0134	-4.79	-0.0101	-5.15	-0.0108	-4.52	-0.0058	-1.64	-0.0138	-4.45	-0.0082	-4.72
HDD squared	0.0007	3.52	0.0005	3.71	0.0003	1.83	0.0002	0.87	0.0008	3.62	0.0004	3.01
Year = 2003	0.0359	5.21	-0.0071	-1.47	-0.0033	-0.56	-0.0143	-1.64	0.0468	6.15	-0.0169	-2.33
Summer 2002	0.0402	3.97	0.0267	3.76	0.0173	2.00	0.0647	5.08	0.0525	4.69	0.0354	5.23
Summer 2003	0.0189	1.87	0.0079	1.11	**-0.0179**	**-2.06**	-0.0558	-4.37	-0.0191	-1.70	-0.0115	-1.68
Unemployment rate											-0.0132	-2.39
Time trend (monthly)											0.0017	2.56
Observations		14,830		15,018		15,018		14,722		14,578		15,018
Customers		37		37		37		37		37		37

Table 5.5 Pooled Regression Results – TOU-8 *Industrial* (share and level equations)

All TOU Customers in One Digit SICs 2 - 4

Log of share used in each daily time period

	Period 1		Period 2		Period 3		Period 4		Period 5			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	0.0026	0.94	-0.0012	-0.54	0.0024	0.52	0.0025	0.63	-0.0014	-0.33		
CDD squared	-0.0003	-2.40	0.0002	1.28	-0.0001	-0.54	-0.0001	-0.51	0.0002	0.72		
HDD	-0.0122	-4.20	0.0003	0.11	0.0027	0.56	-0.0044	-1.06	-0.0063	-1.42		
HDD squared	0.0005	2.86	0.0000	0.11	0.0002	0.60	0.0000	0.04	0.0000	-0.02		
Year = 2003	-0.0154	-1.66	0.0099	1.30	0.0598	3.95	-0.0312	-2.37	-0.0321	-2.28		
Summer 2002	0.1627	11.38	0.0163	1.37	**-0.2945**	**-12.42**	-0.1170	-5.67	0.0062	0.28		
Summer 2003	0.1618	11.71	-0.0484	-4.22	**-0.4121**	**-18.09**	0.0237	1.20	0.1292	6.11		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0212	4.01	0.0222	4.19	0.0258	4.53	0.0239	3.71	0.0200	3.11	0.016	3.21
CDD squared	-0.0013	-4.73	-0.0011	-4.08	-0.0014	-4.74	-0.0013	-3.84	-0.0010	-3.05	-0.001	-3.51
HDD	0.0077	1.41	0.0134	2.45	0.0158	2.69	0.0079	1.19	0.0060	0.91	0.022	4.29
HDD squared	-0.0009	-2.60	-0.0010	-3.03	-0.0008	-2.36	-0.0010	-2.44	-0.0010	-2.48	-0.001	-4.17
Year = 2003	-0.0182	-1.04	0.0061	0.36	0.0561	3.00	-0.0316	-1.50	-0.0324	-1.54	-0.109	-3.88
Summer 2002	0.0615	2.29	-0.0449	-1.66	**-0.3557**	**-12.17**	-0.1742	-5.28	-0.0512	-1.55	-0.082	-3.27
Summer 2003	0.1035	3.98	-0.0815	-3.13	**-0.4452**	**-15.85**	-0.0158	-0.50	0.0895	2.83	-0.064	-2.65
Unemployment rate											-0.022	-2.30
Time trend (monthly)											0.011	4.70
Observations		10,588		10,341		10,341		10,354		10,353		10,588
Customers		27		27		27		27		27		27

Table 5.6 Pooled Regression Results – TOU-8 *Commercial* (share and level equations)

All TOU Customers in One Digit SICs 5 - 7

Log of share used in each daily time period

	Period 1		Period 2		Period 3		Period 4		Period 5			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	0.0010	0.37	0.0046	4.03	0.0038	4.26	-0.0033	-2.16	-0.0072	-4.39		
CDD squared	0.0000	-0.16	-0.0002	-3.60	-0.0003	-5.23	0.0000	0.18	0.0003	3.06		
HDD	0.0001	0.03	-0.0020	-1.59	-0.0031	-3.26	0.0003	0.19	0.0042	2.35		
HDD squared	0.0001	0.53	0.0000	-0.06	0.0000	0.31	0.0001	1.07	0.0000	-0.38		
Year = 2003	-0.0191	-2.48	-0.0089	-2.72	0.0073	2.87	0.0073	1.67	-0.0030	-0.63		
Summer 2002	0.0973	8.28	-0.0155	-3.05	**-0.0278**	**-7.06**	-0.0153	-2.25	0.0154	2.11		
Summer 2003	0.0477	3.97	-0.0199	-3.86	**-0.0311**	**-7.75**	0.0056	0.81	0.0190	2.55		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0098	3.73	0.0196	9.01	0.0200	8.83	0.0129	4.71	0.0090	3.45	0.011	3.71
CDD squared	-0.0006	-3.73	-0.0012	-9.50	-0.0013	-10.24	-0.0010	-6.65	-0.0008	-5.17	0.000	-3.01
HDD	-0.0024	-0.83	-0.0129	-5.46	-0.0138	-5.60	-0.0102	-3.45	-0.0064	-2.25	-0.002	-0.77
HDD squared	0.0000	-0.16	0.0003	1.95	0.0003	1.94	0.0004	2.07	0.0003	1.32	0.000	-0.66
Year = 2003	0.0056	0.73	0.0133	2.13	0.0300	4.61	0.0299	3.80	0.0196	2.61	0.033	2.35
Summer 2002	0.0283	2.43	-0.0490	-5.04	**-0.0653**	**-6.46**	-0.0538	-4.40	-0.0231	-1.98	-0.037	-2.77
Summer 2003	0.0151	1.26	-0.0309	-3.13	**-0.0386**	**-3.75**	-0.0020	-0.16	0.0114	0.96	0.003	0.23
Unemployment rate											-0.078	-7.23
Time trend (monthly)											-0.001	-0.98
Observations		8,143		7,978		7,979		7,979		7,979		8,143
Customers		21		21		21		21		21		21

Consider first the level equations for the GS2T Industrial group. The Summer 2002 and Summer 2003 coefficients suggest a 3.5% increase in average usage in the summer Peak period in 2002 and a 3% reduction in 2003. However, the coefficients for the same variables in the Daily equation indicate that average *daily* usage was higher during the summer months of those years by 4.2% and 1.4% respectively. Thus, as indicated by the share equation results for the same variables, the Peak-period *share* of usage fell by 1% in 2002 and 3.5% and 2003. The only other time period to show such share reduction results was the morning mid-peak period in summer 2003. These results suggest modest price responsive behavior in this group during the summer peak period, with the degree of responsiveness somewhat greater in 2003.

A review of the coefficients for the GS2T Commercial group shows similar, though even more modest evidence of peak-period price response. The peak usage share reduction in summer 2002 was statistically significant, but less than 1%. The level of summer peak usage in 2003 fell by 1.8%, but total daily usage also fell by about the same amount, implying no significant change in the usage share.

The results for the TOU-8 Industrial group show very strong evidence of peak-period price response, confirming the average daily load changes shown in the figures above. The level equations suggest peak period load reductions of 36% in 2002 and 45% in 2003, which are confirmed by the share equations and the fact that average summer daily usage fell by more modest amounts of 8% and 6% in the two years.

The results for the TOU-8 Commercial group show significant but more modest peak-period price response, with load reductions of 6.5% and 3.9% in 2002 and 2003 respectively, compared to an average daily reduction of 3.7% in 2002 and no change in 2003.

Web hits results. Tables 5.7 through 5.10 show results for expanded regressions in which a variable was included to represent consumers' use of the SCE Energy Manager system on their electricity usage patterns. The specific variable used was each customer's cumulative recorded monthly web hits as measured by SCE over the period of March 2002 through October 2003. The variable was designed to capture the possible effect of repeated use of the EM website over time on actions taken to modify usage patterns.

The results for the GS2T Industrial customers indicate a significant negative relationship between website usage and total daily usage, as well as average usage in each time period. However, the share equation shows no relative effect of web usage on peak-period consumption. At the mean value of the cumulative web hits variable (11), the estimated coefficient implies an approximately 1 percent reduction in daily usage. The results for the GS2T Commercial customers also indicate a significant, though smaller negative effect of website usage on total daily usage. However, the effect appears to be focused relatively most strongly in the morning off-peak period.

The results for the TOU-8 Industrial group were similar to the industrial customers above, with a small negative relationship between web hits and total daily usage.

Table 5.7 Web Hits Results – GS2T *Industrial* (share and level equations)

All GS2T Customers in One Digit SICs 2 - 4 -0.00992

Log of share used in each daily time period

	Period 1		Period 2		Period 3		Period 4		Period 5	
lnkwsh	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	-0.0012	-0.83	0.0016	1.23	0.0026	2.16	-0.0059	-2.66	-0.0089	-3.66
CDD squared	0.0002	2.02	-0.0001	-1.24	-0.0002	-3.61	0.0001	0.90	0.0002	1.72
HDD	0.0001	0.05	0.0029	1.89	-0.0004	-0.26	-0.0077	-2.86	-0.0091	-3.04
HDD squared	0.0002	1.34	-0.0001	-0.88	-0.0001	-0.96	0.0004	1.80	0.0005	2.33
Year = 2003	-0.0158	-3.49	0.0108	2.78	0.0228	6.25	-0.0028	-0.41	-0.0288	-3.85
Summer 2002	-0.0061	-0.92	-0.0066	-1.16	-0.0100	-1.88	0.0781	7.90	0.0961	8.83
Summer 2003	0.0390	5.99	-0.0258	-4.62	-0.0349	-6.65	0.0013	0.14	0.0198	1.84
Cumulative Web hits	0.0000	0.23	0.0001	0.94	0.0002	1.64	**-0.0005**	**-2.73**	**-0.0005**	**-2.25**

Log of usage level in each time period

											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0064	3.30	0.0094	5.49	0.0105	5.98	0.0019	0.70	-0.0011	-0.38	0.0084	6.11
CDD squared	-0.0001	-1.00	-0.0004	-3.84	-0.0005	-5.35	-0.0002	-1.07	0.0000	-0.25	-0.0003	-3.91
HDD	0.0016	0.68	0.0042	2.01	0.0009	0.43	-0.0063	-1.89	-0.0077	-2.14	0.0012	0.72
HDD squared	0.0000	0.05	-0.0003	-1.66	-0.0003	-1.66	0.0002	0.79	0.0004	1.33	-0.0002	-1.35
Year = 2003	0.0042	0.72	0.0317	6.09	0.0437	8.18	0.0179	2.13	-0.0081	-0.90	0.0378	5.50
Summer 2002	0.0390	4.51	0.0371	4.88	0.0334	4.28	0.1215	9.90	0.1395	10.66	0.0434	6.68
Summer 2003	0.0478	5.59	-0.0197	-2.62	-0.0289	-3.75	0.0077	0.63	0.0261	2.02	0.0134	2.10
Unemployment rate	--		--		--		--		--		-0.0036	-0.72
Time trend (monthly)	--		--		--		--		--		-0.0021	-3.22
Cumulative Web hits	-0.0013	-7.57	-0.0013	-8.13	-0.0012	-7.50	-0.0019	-7.66	-0.0019	-6.99	**-0.0013**	**-10.44**
Obs		23,002		22,999		23,000		22,999		22,999		23,002
Customers		57		57		57		57		57		57

Table 5.8 Web Hits Results – GS2T *Commercial* (share and level equations)

All GS2T Customers in One Digit SICs 5 - 7

Log of share used in each daily time period

	Period 1		Period 2		Period 3		Period 4		Period 5	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	-0.0048	-2.20	-0.0009	-1.01	0.0057	6.03	-0.0019	-0.85	-0.0074	-3.46
CDD squared	-0.0001	-1.21	0.0001	2.44	-0.0001	-2.11	0.0002	1.58	0.0001	0.70
HDD	-0.0052	-1.96	-0.0016	-1.49	-0.0023	-1.98	0.0027	0.98	-0.0057	-2.21
HDD squared	0.0004	1.83	0.0001	1.81	-0.0001	-0.86	-0.0002	-0.80	0.0005	2.41
Year = 2003	0.0419	6.40	-0.0052	-1.98	-0.0013	-0.47	-0.0138	-2.06	0.0490	7.63
Summer 2002	0.0109	1.14	0.0004	0.11	-0.0091	-2.19	0.0396	4.04	0.0261	2.78
Summer 2003	0.0367	3.84	0.0216	5.55	-0.0041	-1.00	-0.0394	-4.01	0.0009	0.09
Cumulative Web hits	-0.0009	-5.38	0.0001	1.79	0.0001	1.42	0.0005	2.57	0.0000	0.26

Log of usage level in each time period

											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0087	3.76	0.0125	7.64	0.0191	9.65	0.0116	3.99	0.0065	2.54	0.0129	8.89
CDD squared	-0.0003	-2.13	0.0000	0.02	-0.0002	-2.09	0.0001	0.42	-0.0001	-0.40	-0.0001	-1.10
HDD	-0.0136	-4.86	-0.0101	-5.16	-0.0108	-4.53	-0.0058	-1.63	-0.0138	-4.46	-0.0082	-4.74
HDD squared	0.0007	3.57	0.0005	3.72	0.0003	1.84	0.0002	0.86	0.0008	3.63	0.0004	3.03
Year = 2003	0.0409	5.91	-0.0064	-1.32	-0.0026	-0.43	-0.0150	-1.71	0.0477	6.23	-0.0170	-2.34
Summer 2002	0.0369	3.64	0.0263	3.69	0.0168	1.94	0.0652	5.11	0.0519	4.63	0.0347	5.12
Summer 2003	0.0222	2.20	0.0084	1.17	-0.0173	-2.00	-0.0563	-4.40	-0.0185	-1.64	-0.0110	-1.60
Unemployment rate											-0.0130	-2.36
Time trend (monthly)											0.0019	2.79
Cumulative Web hits	-0.0012	-6.68	-0.0002	-1.31	-0.0002	-1.20	0.0002	0.77	-0.0002	-1.12	**-0.0003**	**-2.84**
Obs		14,830		15,018		15,018		14,722		14,578		15,018
Customers		37		37		37		37		37		37

Table 5.9 Web Hits Results – TOU-8 *Industrial* (share and level equations)

All GS2T Customers in One Digit SICs 2 - 4

Log of share used in each daily time period	Period 1		Period 2		Period 3		Period 4		Period 5			
lnkwsh	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	0.0025	0.88	-0.0013	-0.55	0.0020	0.44	0.0027	0.68	-0.0013	-0.30		
CDD squared	-0.0003	-2.34	0.0002	1.29	-0.0001	-0.47	-0.0001	-0.56	0.0002	0.69		
HDD	-0.0120	-4.13	0.0003	0.12	0.0031	0.65	-0.0046	-1.11	-0.0064	-1.45		
HDD squared	0.0005	2.81	0.0000	0.10	0.0002	0.54	0.0000	0.07	0.0000	0.01		
Year = 2003	-0.0217	-2.25	0.0087	1.10	0.0455	2.88	-0.0237	-1.72	-0.0268	-1.83		
Summer 2002	0.1627	11.38	0.0162	1.36	-0.2949	-12.45	-0.1168	-5.66	0.0063	0.29		
Summer 2003	0.1600	11.56	-0.0486	-4.24	-0.4152	-18.22	0.0254	1.28	0.1304	6.16		
Cumulative Web hits	0.0006	2.40	0.0001	0.53	0.0013	3.23	-0.0007	-1.95	-0.0005	-1.29		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0213	4.04	0.0222	4.19	0.0255	4.47	0.0242	3.75	0.0202	3.14	0.0156	3.16
CDD squared	-0.0013	-4.75	-0.0011	-4.08	-0.0014	-4.69	-0.0013	-3.88	-0.0010	-3.07	-0.0009	-3.48
HDD	0.0076	1.38	0.0133	2.45	0.0162	2.75	0.0076	1.15	0.0058	0.87	0.0216	4.27
HDD squared	-0.0009	-2.58	-0.0010	-3.02	-0.0009	-2.41	-0.0010	-2.41	-0.0010	-2.46	-0.0013	-4.13
Year = 2003	-0.0137	-0.76	0.0067	0.37	0.0435	2.23	-0.0218	-0.99	-0.0249	-1.13	-0.1104	-3.93
Summer 2002	0.0615	2.29	-0.0449	-1.66	-0.3560	-12.19	-0.1740	-5.27	-0.0510	-1.55	-0.0803	-3.22
Summer 2003	0.1048	4.03	-0.0814	-3.12	-0.4479	-15.94	-0.0137	-0.43	0.0912	2.88	-0.0624	-2.58
Unemployment rate	--		--		--		--		--		-0.0195	-2.07
Time trend (monthly)	--		--		--		--		--		0.0130	5.30
Cumulative Web hits	-0.0004	-0.90	-0.0001	-0.11	0.0012	2.31	-0.0009	-1.58	-0.0007	-1.22	**-0.0014**	**-3.33**
Obs		10,588		10,341		10,341		10,354		10,353		10,588
Customers		27		27		27		27		27		27

Table 5.10 Web Hits Results – TOU-8 *Commercial* (share and level equations)

All GS2T Customers in One Digit SICs 5 - 7

Log of share used in each daily time period	Period 1		Period 2		Period 3		Period 4		Period 5			
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat		
CDD	0.0013	0.50	0.0047	4.08	0.0035	3.95	-0.0031	-2.06	-0.0071	-4.32		
CDD squared	0.0000	-0.20	-0.0002	-3.62	-0.0003	-5.13	0.0000	0.15	0.0003	3.04		
HDD	-0.0002	-0.05	-0.0020	-1.62	-0.0029	-3.06	0.0002	0.13	0.0041	2.30		
HDD squared	0.0001	0.58	0.0000	-0.04	0.0000	0.19	0.0001	1.11	0.0000	-0.35		
Year = 2003	-0.0133	-1.68	-0.0080	-2.35	0.0028	1.06	0.0098	2.17	-0.0011	-0.24		
Summer 2002	0.0945	8.01	-0.0160	-3.13	-0.0255	-6.47	-0.0165	-2.43	0.0145	1.98		
Summer 2003	0.0476	3.97	-0.0199	-3.86	-0.0311	-7.77	0.0056	0.81	0.0190	2.55		
Cumulative Web hits	-0.0002	-2.86	0.0000	-1.09	0.0001	6.85	-0.0001	-2.19	-0.0001	-1.49		
Log of usage level in each time period											Total Daily Usage	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
CDD	0.0102	3.88	0.0199	9.12	0.0200	8.80	0.0133	4.85	0.00935	3.58	0.0105	3.72
CDD squared	-0.0006	-3.78	-0.0012	-9.55	-0.0013	-10.23	-0.0010	-6.70	-0.00076	-5.21	-0.0005	-3.01
HDD	-0.0027	-0.94	-0.0131	-5.54	-0.0137	-5.58	-0.0105	-3.53	-0.00661	-2.34	-0.0024	-0.78
HDD squared	0.0000	-0.10	0.0003	2.00	0.0003	1.93	0.0004	2.13	0.00026	1.37	-0.0001	-0.64
Year = 2003	0.0128	1.62	0.0177	2.74	0.0291	4.33	0.0361	4.44	0.02513	3.24	0.0334	2.35
Summer 2002	0.0248	2.12	-0.0512	-5.26	-0.0649	-6.39	-0.0569	-4.64	-0.02587	-2.22	-0.0372	-2.81
Summer 2003	0.0150	1.26	-0.0310	-3.13	-0.0386	-3.75	-0.0021	-0.17	0.01135	0.96	0.0029	0.21
Unemployment rate	--		--		--		--		--		-0.0780	-7.22
Time trend (monthly)	--		--		--		--		--		-0.0011	-0.85
Cumulative Web hits	-0.0002	-3.60	-0.0001	-2.69	0.0000	0.51	-0.0002	-3.01	-0.00015	-2.82	-0.00004	-0.64
Obs		8,143		7,978		7,979		7,979		7,979		8,143
Customers		21		21		21		21		21		21

It is important to note that it is difficult to draw conclusions about causality regarding the negative relationship between the web hits measure and total daily usage, especially in view of the lack of a significant separate effect on usage or usage shares in the peak period.

Individual customer price responsiveness. Figures 5.8 through 5.11 show the distributions of the coefficients on the variable *Summer * D2003* in the peak-period *share* and *level* equations in the individual customer regressions for each of the customer groups. We believe that the combination of these coefficients represents the most reliable indicator of TOU price responsive behavior in the form of reductions in average summer peak-period usage relative to usage in the other time periods. For example, a large negative value of the peak period coefficient in the *level* equation may represent TOU price response, although it can also come in conjunction with negative coefficients in each time period, which would signal an overall reduction in summer usage. However, a negative coefficient in the *level* equation, combined with a negative coefficient in the peak *share* equation, indicates both an absolute reduction in summer peak period usage and a reduction relative to the other periods.

Separate graphs are shown for the two rate classes and two broad SIC categories, with results shown separately for the EM and No EM groups (in the left and right-hand portions of the graphs) in the case of GS2T. The graphs were sorted by the coefficient values in the share equations. The graphs confirm the results from the pooled estimation. The TOU-8 customers were substantially more price responsive than the GS2T customers, and the industrial customers tended to be more responsive than the commercial customers. The graphs illustrate a typical finding in terms of the range of price responsiveness across customers in a given group. That is, for the GS2T groups, a relatively small fraction of customers (10 to 20 percent) tended to be moderately to highly price responsive, while as much as a majority of customers tended to show little if any price responsiveness. In contrast, as many as half of the accounts in the TOU-8 groups appeared to be price responsive. These findings are confirmed in Table 5.11 below.

Table 5.11 Estimated Price Responsiveness by Rate Class and SIC Group

SIC group	Number	% significantly price responsive		Average % change of price responders in: Share of daily summer peak usage		Level of summer peak usage		Number of webhits Ave.	Max
		2002	2003	2002	2003	2002	2003		
GS2T									
20	13	0%	8%	-2%	-1%	-3%	-4%	37	168
30	9	44%	22%	-12%	-5%	-11%	-16%	4	8
31-39	30	23%	20%	-8%	-25%	-9%	-29%	29	46
50-70	35	29%	14%	-4%	2%	-6%	-8%	12	20
TOU-8									
20-30	19	42%	53%	-40%	-43%	-60%	-46%	31	95
4941	3	100%	100%	-192%	-249%	-138%	-229%	50	98
50-70	16	31%	31%	-9%	-8%	-9%	-15%	226	655

Figure 5.8 Distribution of Price Response Coefficients – *GS2T Industrial* (EM and No EM)

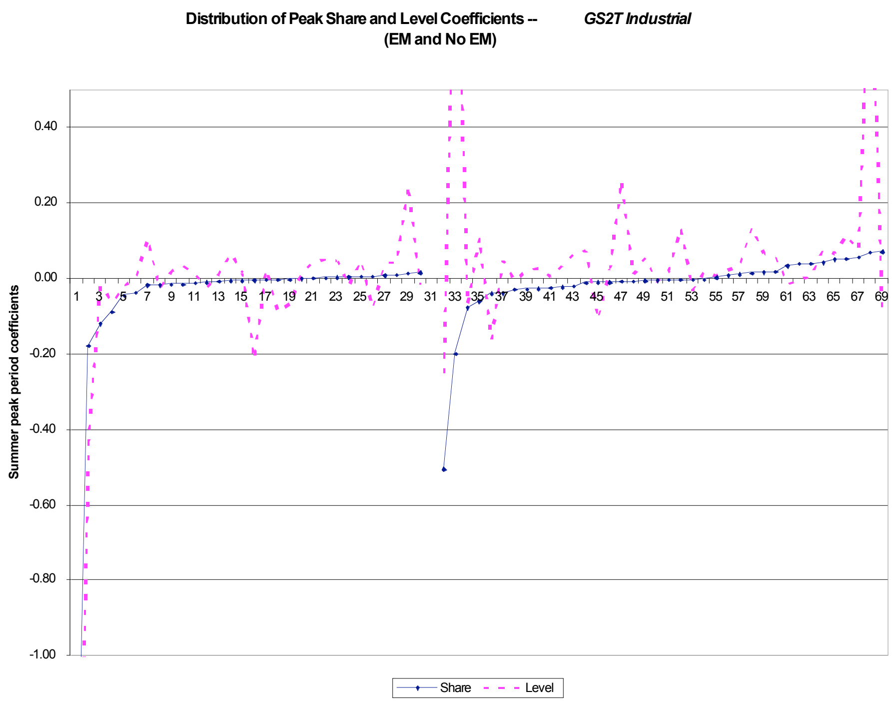


Figure 5.9 Distribution of Price Response Coefficients – *GS2T Commercial* (EM and No EM)

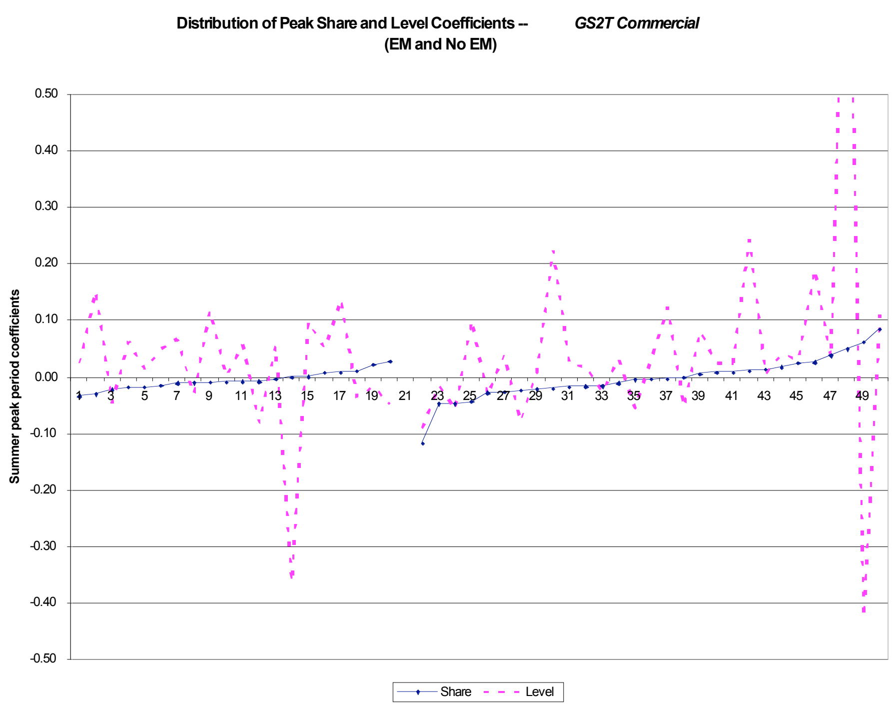


Figure 5.10 Distribution of Price Response Coefficients – *TOU-8 Industrial*

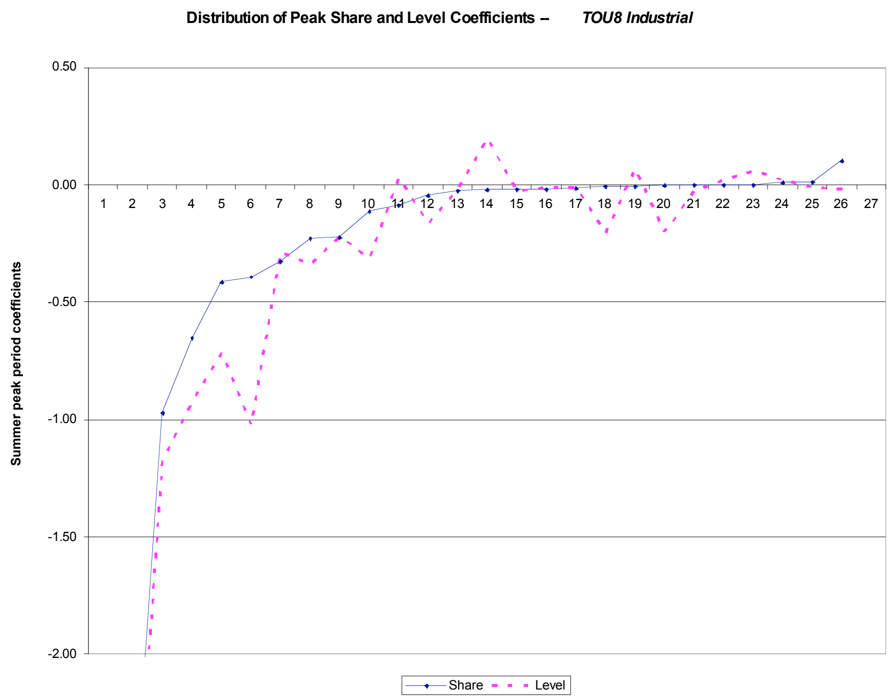
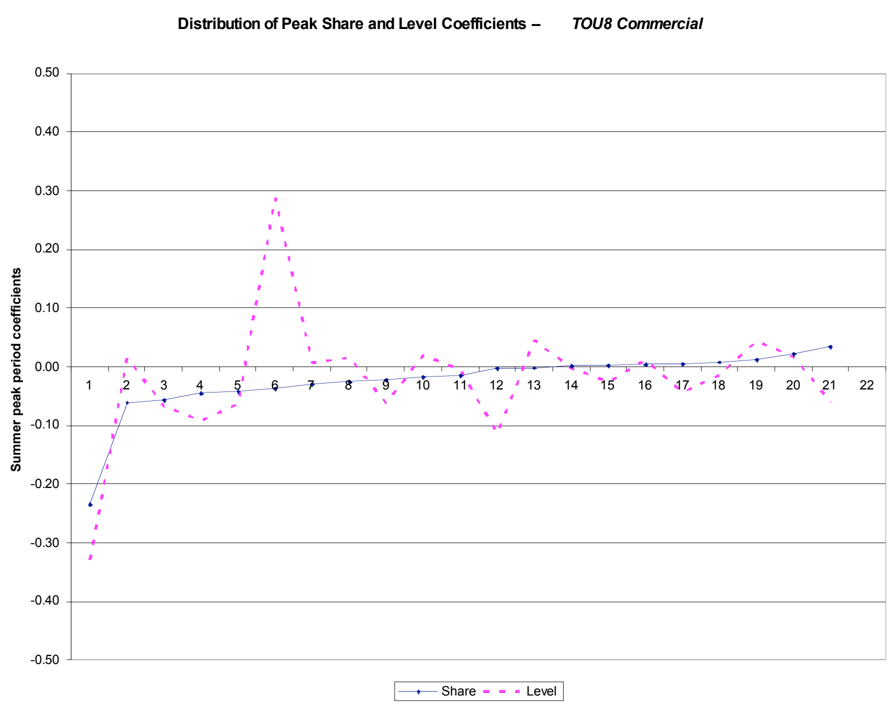


Figure 5.11 Distribution of Price Response Coefficients – TOU-8 *Commercial*



Price Responsiveness by SIC Group

Table 5.11 shows the percentage of customers judged to be price responsive in several industrial and commercial SIC categories for which a reasonable number of accounts were available. The table also shows the estimated average percentage reduction in both the share of daily usage in the summer peak period and the level of summer peak usage, for both 2002 and 2003, and the average and maximum number of web hits recorded for the customers in each group.

These results again confirm that the TOU-8 customers were more price responsive than the GS2T customers, and that the industrial customers were more price responsive than commercial customers. The GS2T SIC group 30, which includes businesses in the plastics industry, was one of the most price responsive groups. In addition, the TOU-8 water supply customers (SIC 4941) were extremely price responsive, often reducing usage to near zero during the summer peak period.[8] These sites presumably have storage capabilities and multiple pumps that make them extremely flexible in managing their usage pattern. Finally, there appeared to be no consistent patterns of differences between 2002 and 2003.

The number of web hits varied considerably across customers in each group, as indicated by the difference between the average and maximum values for some of the groups. There appears to be no clear pattern of, for example, the most frequent web users being the most price-responsive. However, as indicated in the econometric results reported above, some effect of web hits on price responsiveness was found.

Aggregate TOU Price Response

We used the estimated coefficient results from the individual customer regressions to develop an estimate of the aggregate TOU price response of the class of customers represented by the survey sample used in the analysis. To do so, we needed to make a number of assumptions and approximations. This was the case because the population-level data on customer accounts and sales provided by SCE was at the total rate-class level, while the customer accounts used in the analysis represented only a portion of that population (*e.g.*, only those in SICs 2 through 7). We used information from our analysis of PG&E data, described in Section 6, to approximate the portion of the total population to which the survey sample results should be expanded.

We also needed to establish a screening rule for determining how to apply the estimated price response coefficients to calculate an implied amount of summer peak-period load reduction. We used a relatively conservative rule of calculating load reductions only for those customer accounts with negative and significant peak-period coefficients for both the share and level equations. In those cases we applied the peak share coefficient to the actual average peak load to calculate the amount of implied load reduction from the baseline level that would otherwise have

[8] By the form of the logarithmic estimating equation, the coefficient on the summer indicator variable for a particular year represents percentage load changes as Ln (Lnew/Lold), where Lnew represents the actual summer peak load, and Lold represents the weather-adjusted load that would have occurred in a non-summer month. This form of calculating percentage changes produces values very close to the more conventional (Lnew-Lold)/Lold for small load changes. However, for large changes, the result can be a value greater than 100%, as seen in the table for SIC 4941. This is the case since the log-ratio approach to calculating percentages is analogous to using the *average* of the actual and baseline loads as the denominator in the more conventional definition, which can produce a value greater than 100% for large differences between the baseline and actual loads.

been reached. This has the effect of calculating load reductions only for those customers toward the left side of the distributions in Figures 5.8 – 5.11. The results of these calculations are shown in Table 5.12.

Table 5.12 Aggregate TOU Peak Load Response by Rate Class and SIC Group

SCE	Ave. Peak Demand (MW)	Estimated TOU peak reduction	% Reduction
GS2T			
Industrial	783	19.2	2.4%
Commercial	479	3.5	0.7%
Total	1,263	22.7	1.8%
TOU-8			
Industrial	743	119.4	13.8%
Commercial	1,007	23.1	2.2%
Total	1,750	142.5	7.5%

Thus, for example, we estimate that the GS2T industrial customers reduced their summer peak usage in 2003 by 2.4 percent, or approximately 19 MW, while the TOU-8 industrial customers reduced their summer peak usage by nearly 14 percent, or nearly 120 MW.

We suggest that the estimate for the TOU-8 industrial customers in particular be regarded as having a fairly wide confidence interval. This is the case because of the relatively small sample size (approximately 30) and the resulting uncertainty about whether the several extremely price responsive customers in the sample were truly representative of the population. As will be seen in Section 6, the estimated aggregate peak TOU price responsiveness for comparable customers at PG&E was substantially lower. That is, a similar pattern of results was obtained in terms of the large industrial customers having the largest percentage of price responders, and the largest responders in absolute terms. However, the aggregate peak load reduction was estimated to be closer to 4.5 percent than 14 percent.

Case Studies—Individual Customer Examples

A number of graphs are provided in the appendix to this section, which illustrate examples of load profiles for a variety of individual customer accounts in both the GS2T and TOU-8 rate classes, and for customers that were EM users or non-users at the time of the SCE survey. Each figure contains four 24-hour weekday load profiles, each representing an average across weekdays in May (when non-summer energy and demand charges apply) and June (when the Peak TOU energy and demand charges apply), for both 2002 and 2003. As an aid in interpreting the graphs, the two May loads are shown as dashed lines, and the two loads for 2003 are shown in a lighter shade than those in 2002. Also shown in text boxes in the lower right-hand corner of each graph is information about each customer drawn from several sources. The following information is provided:

- Two-digit SIC code,
- EM user status, and if a user, the customer's response to two survey questions about whether they claimed to use the EM tools to shift energy (kWh) or demand (kW) away from the peak period,

- The estimated price response (PR) coefficients for the summer peak period in the share equation, for both 2002 and 2003, and
- The total number of EM web hits recorded by SCE.

The load profiles illustrate several aspects of the energy use patterns of these customers. First, they demonstrate the wide variety of load patterns across customer types. Second, the GS2T customers for the most part show little obvious evidence of peak-period price response. At the same time, several of the TOU-8 customers show dramatic evidence of peak-period load reductions. For the most part, the load profiles confirm the price response coefficients estimated in the econometric analysis. However, the average load profiles cannot capture the day-to-day variability in the data that underlie the regression estimates.

The selected customer accounts include some of the most clear and dramatic examples of customers reducing load during the peak period, and sometimes shifting it to other hours of the day. These examples should not be considered typical of the majority of accounts.

Conclusions

The following conclusions may be drawn from the above range of analyses:

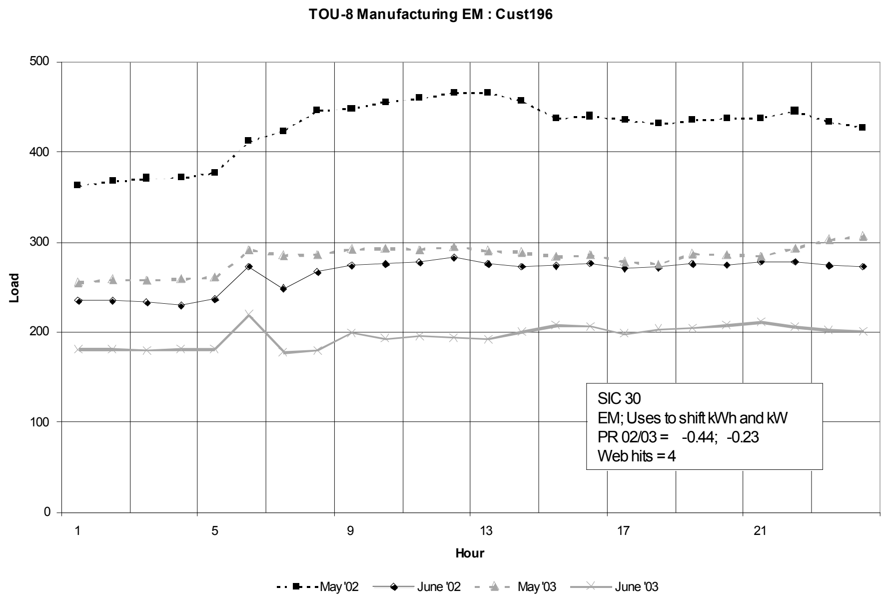
1. The TOU-8 customers on average respond in significant and substantial degrees to the higher energy and demand charges that they face in the summer peak time period relative to other time periods of the year. They reduce average usage in the summer peak period relative to usage in other summer time periods and in the same period in non-summer months.
2. Customers in the Industrial group (SIC codes between 2 and 4) show greater price responsiveness than those in the Commercial group (SIC codes between 5 and 7), which is as expected.
3. Some GS2T customers reduce relative usage in the summer peak period in significant but modest degrees. However, it is not possible to definitively attribute those load changes to the relatively small TOU peak-period energy price differential that they faced after receiving the RTEM equipment, as they already faced an implicit higher price during their own summer peak periods due to the summer demand charge that applied before and after the change to TOU energy prices. Like the TOU-8 class, customers in the Industrial group were more price responsive than those in the Commercial group.
4. There is some evidence that cumulative use of the SCE EnergyManager website was associated with lower average daily consumption among GS2T customers. However, this lower daily usage did not imply reductions in the peak period.
5. It is difficult to draw conclusions about any systematic change in price responsiveness between 2002 and 2003, such as might be expected from longer experience facing the TOU energy prices (for GS2T customers) or taking advantage of the EM website tools.
6. The individual customer price responsiveness results indicate that the percentage of price responsive customers ranged from 20 to 30% of the GS2T customers, and 30 to 50% of the TOU-8 customers in the broad SIC groupings.

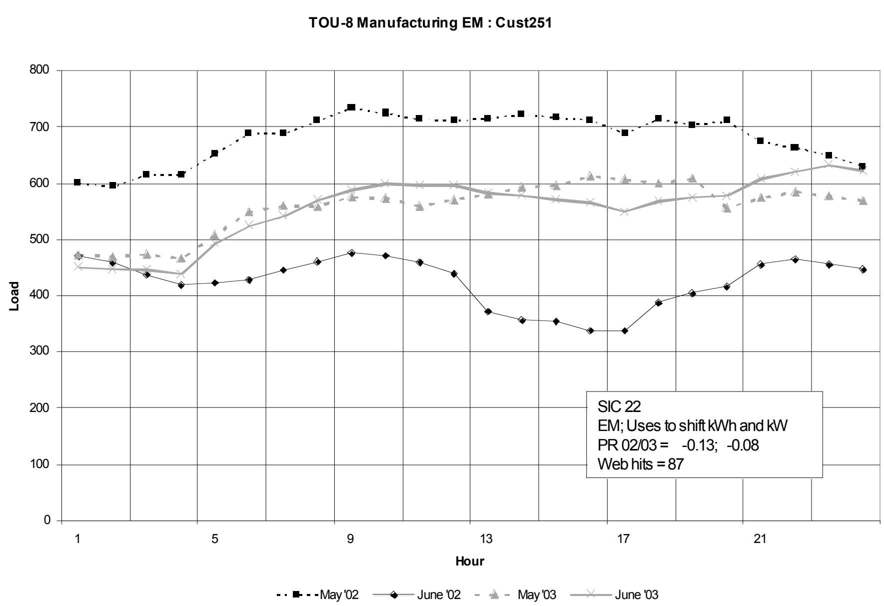
In summary, we found evidence in the interval load data of customer response to TOU prices, particularly the large summer peak-period price premium for TOU-8 customers, and also to a lesser extent for the smaller GS2T customers that were switched to a TOU rate. There is also evidence from the SCE survey that a large fraction of the survey respondents reported using the EM website to help them take actions to reduce on-peak usage.

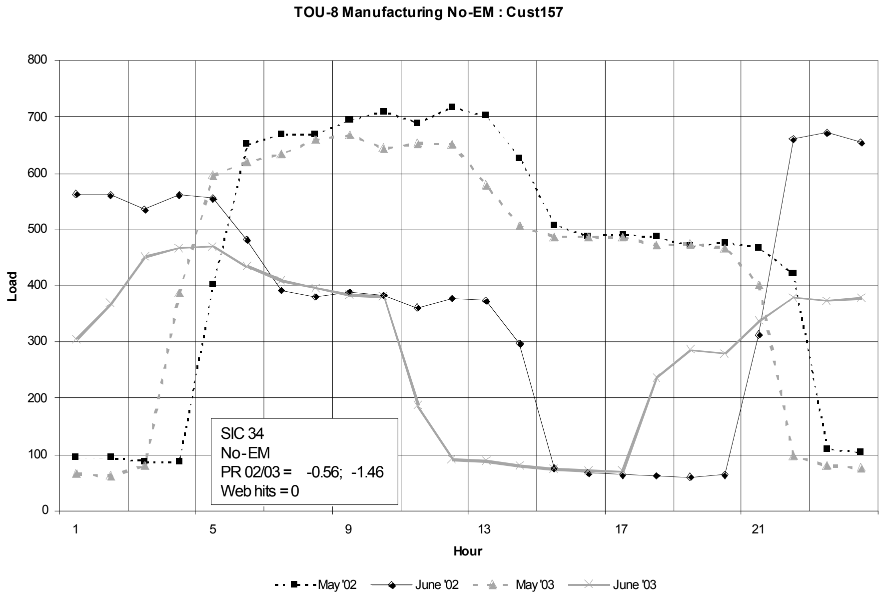
However, given the lack of before-period usage data, or usage for a control group of comparable customers that did not receive the RTEM equipment or receive TOU prices, we cannot attribute the TOU price response behavior observed in the data to the installation of the RTEM equipment. The large summer peak prices faced by the TOU-8 customers existed prior to the RTEM installations, implying that the observed peak-period load reductions were occurring previously. Furthermore, there is no strong evidence that access to the EM website enhanced their price responsive behavior. There is similarly little evidence that GS2T customer use of the EM website led to significant changes in peak-period usage.

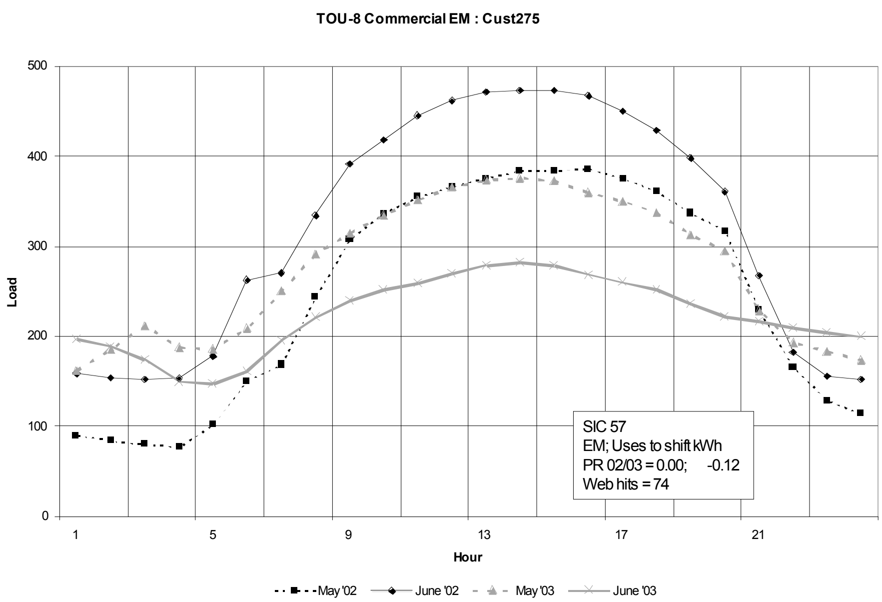
The TOU price responsiveness results, particularly those for the TOU-8 customers have one important implication regarding the topic of demand response in California. The current tariff imposes high prices during the defined summer peak period on every weekday during the months of June through September. The fact that a number of TOU-8 customers make sufficient changes to their daily operations to produce significant and substantial changes to their peak-period usage suggests a fair degree of load flexibility. If the current tariff were altered to a version of a *critical peak pricing* product that sent high peak prices only on days with critical resource constraint conditions, and lower peak prices on lower-cost days, then these customers could continue to provide substantial demand response on days on which it was most valuable, but could take advantage of lower peak prices on days of lower cost by not having to modify their operations.

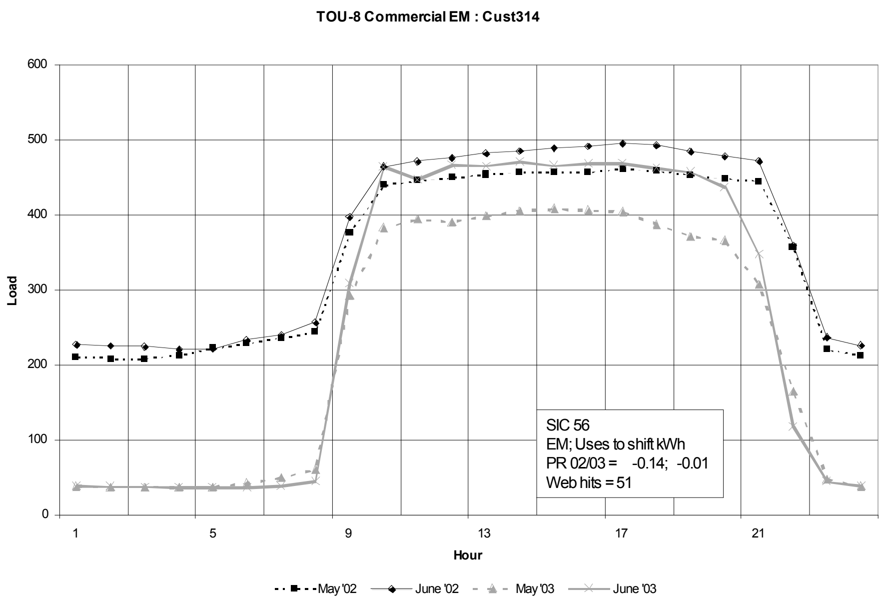
Appendix to Section 5



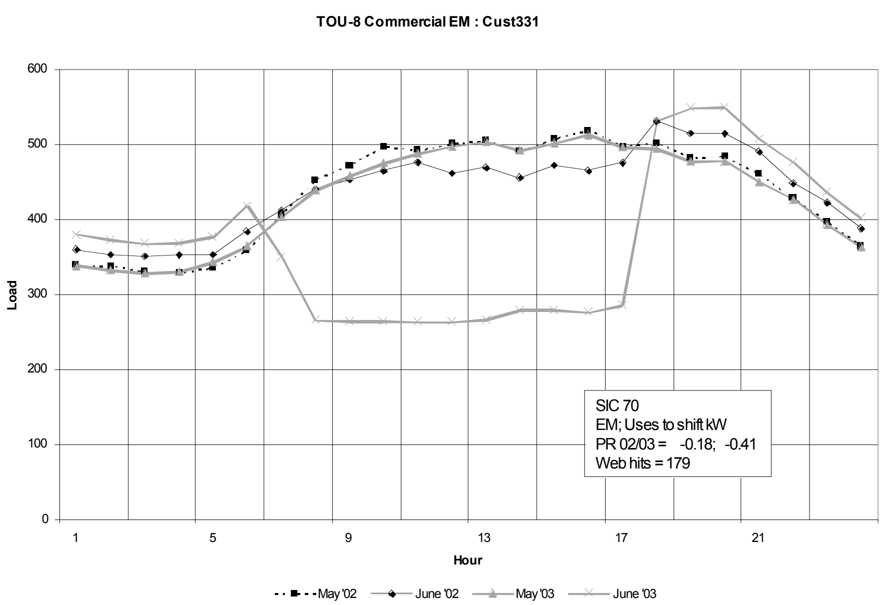



TOU-8 Manufacturing No-EM : Cust157
Load
Hour
SIC 34
No-EM
PR 02/03 = -0.56; -1.46
Web hits = 0
May '02
June '02
May '03
June '03

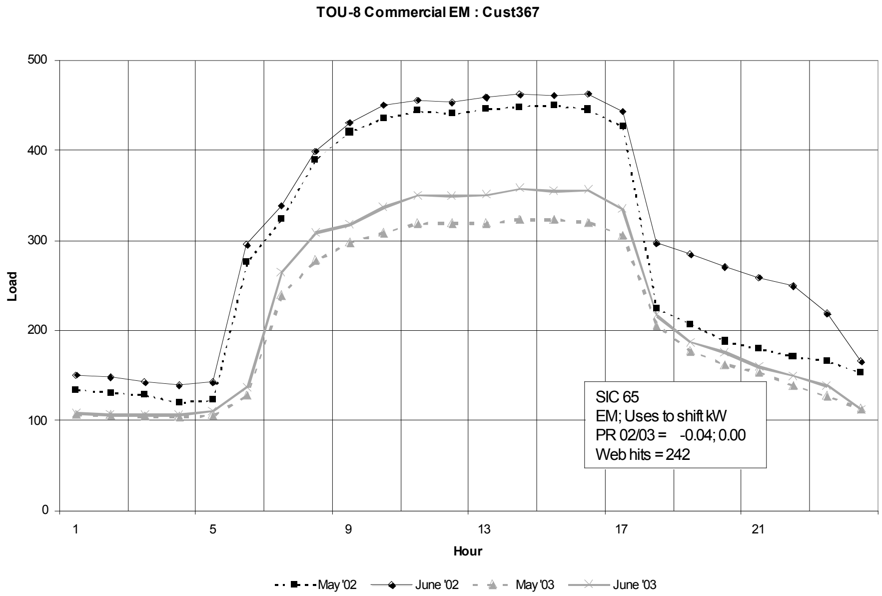

TOU-8 Commercial EM : Cust275
Load
Hour
SIC 57
EM; Uses to shift kWh
PR 02/03 = 0.00; -0.12
Web hits = 74
May '02
June '02
May '03
June '03

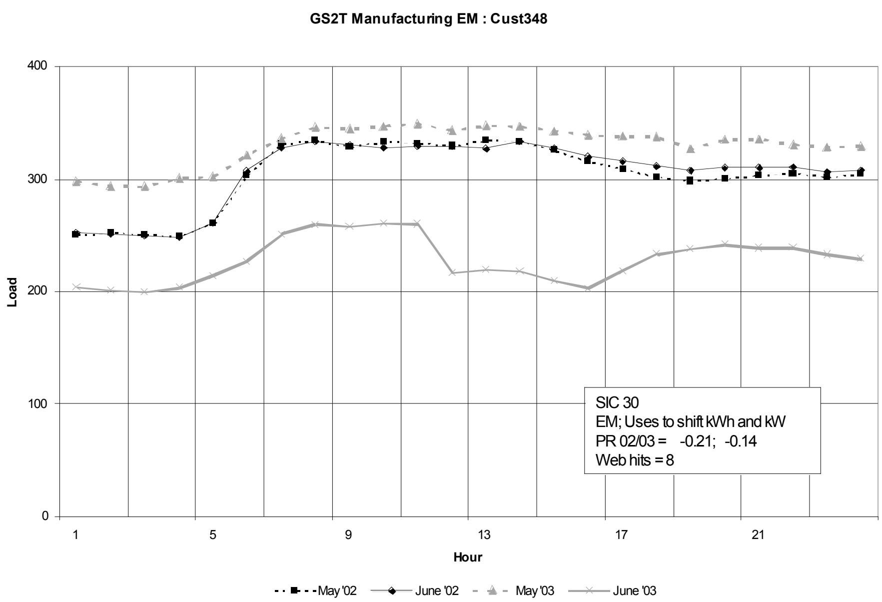


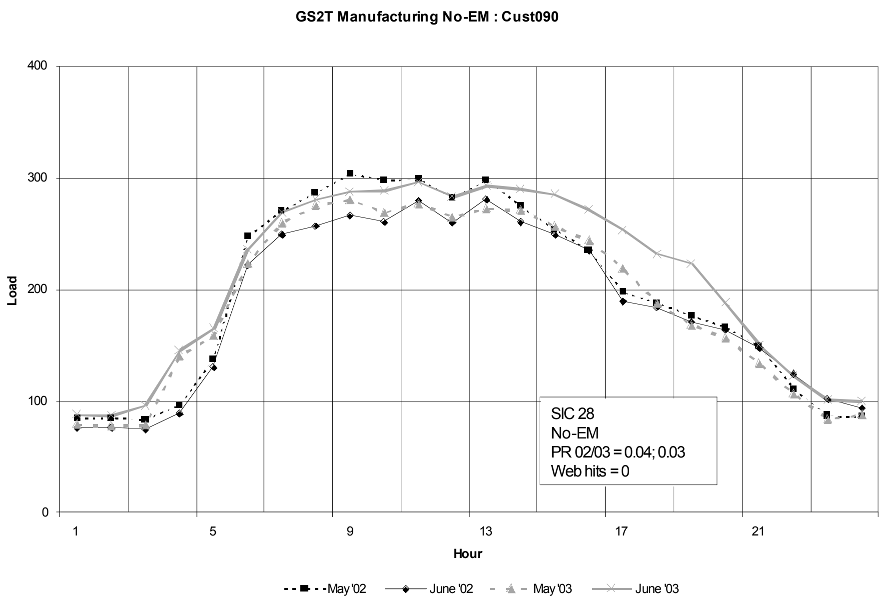
TOU-8 Commercial EM : Cust314
600
500
400
300
200
100
0
Load
1
5
9
13
17
21
Hour
SIC 56
EM; Uses to shift kWh
PR 02/03 = -0.14; -0.01
Web hits = 51
May '02
June '02
May '03
June '03

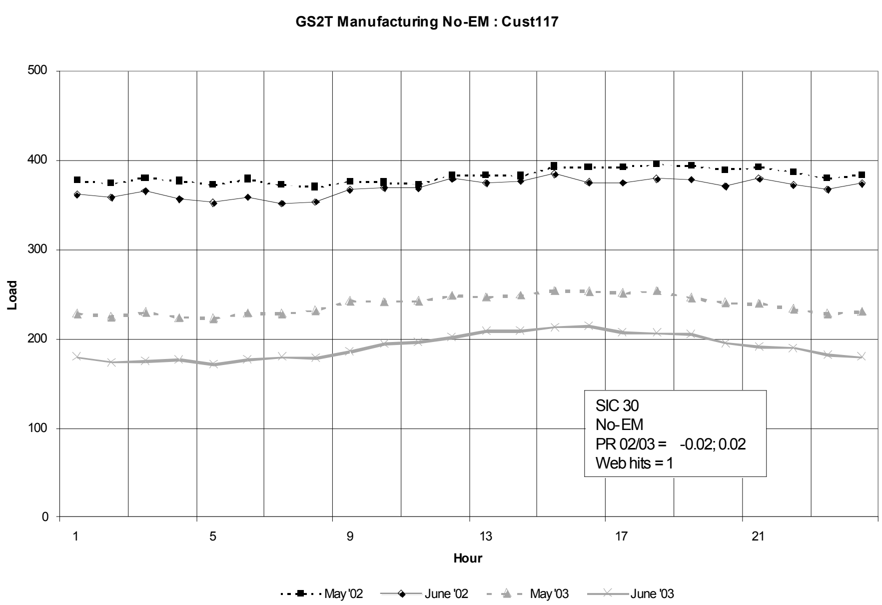


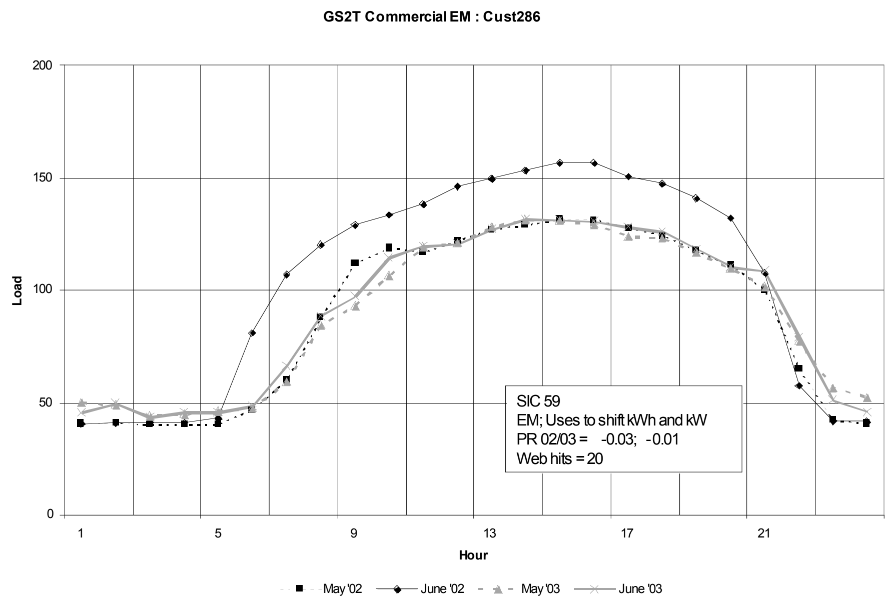
TOU-8 Commercial EM : Cust331
600
500
400
300
200
100
0
Load
1
5
9
13
17
21
Hour
SIC 70
EM; Uses to shift kW
PR 02/03 = -0.18; -0.41
Web hits = 179
May '02
June '02
May '03
June '03

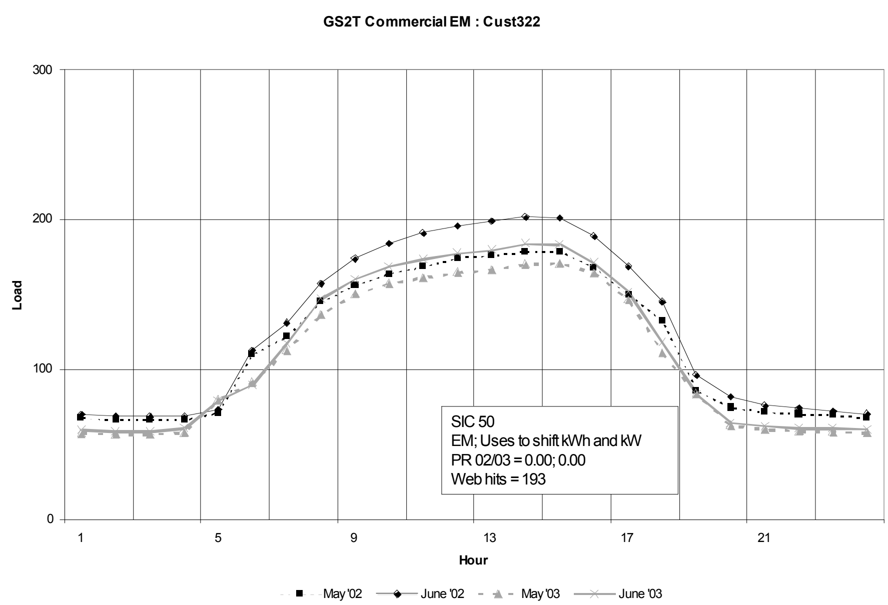

TOU-8 Commercial EM : Cust367
Load
Hour
SIC 65
EM; Uses to shift kW
PR 02/03 = -0.04; 0.00
Web hits = 242
May '02
June '02
May '03
June '03


GS2T Manufacturing EM : Cust348
Load
Hour
SIC 30
EM; Uses to shift kWh and kW
PR 02/03 = -0.21; -0.14
Web hits = 8
May '02
June '02
May '03
June '03


GS2T Manufacturing No-EM : Cust090
Load
Hour
SIC 28
No-EM
PR 02/03 = 0.04; 0.03
Web hits = 0
May '02
June '02
May '03
June '03


GS2T Manufacturing No-EM : Cust117
Load
Hour
SIC 30
No-EM
PR 02/03 = -0.02; 0.02
Web hits = 1
May '02
June '02
May '03
June '03


GS2T Commercial EM : Cust286
Load
Hour
SIC 59
EM; Uses to shift kWh and kW
PR 02/03 = -0.03; -0.01
Web hits = 20
May '02
June '02
May '03
June '03


GS2T Commercial EM : Cust322
Load
Hour
SIC 50
EM; Uses to shift kWh and kW
PR 02/03 = 0.00; 0.00
Web hits = 193
May '02
June '02
May '03
June '03

EVALUATION OF RTEM AT PG&E

Introduction

Under RTEM (AB29X), Pacific Gas and Electric (PG&E) installed new advanced metering equipment for all customer accounts with billing demands greater than 200 kW, but less than 500 kW. For customers above that level, the utility generally already maintained interval metering equipment, and only needed to install communication equipment necessary to interrogate the meters on a daily basis to make customers' load data available on a website. The less than 500 kW customers generally took service under PG&E's A10 rate, which featured flat seasonal energy prices and seasonal all-hours demand charges, as described in section 6.3 below. After receiving the RTEM equipment, these customers were switched to a new A10 TOU rate that maintained the demand charges, but added seasonal TOU energy prices. Customers with billing demands in excess of 500 kW generally faced PG&E's E19 (for customer accounts less than 1,000 kW) or E20 (for accounts in excess of 1,000 kW), which already contained TOU demand and energy charges. PG&E also set up (through a third party) the InterAct website, by which customers could access their hourly load data on a daily basis. Customers were invited to set up an account, but accounts were not automatically established for all RTEM customers.

Data Provided

Between spring and summer 2004, PG&E provided several sets of data relevant to the RTEM evaluation. These data included the following:

- Interval load data for all customers receiving AB29X metering equipment, from 2001 (or when data became available) through 2003;
- Monthly billing data for the same customers, for 2001 through 2003, which also contained information on direct access status, SIC codes and ZIP codes (for matching accounts to weather stations);
- Meter installation data, providing dates of installation;
- InterAct login data, providing information on dates on which InterAct accounts were activated and the most recent date on which the website was used to access data.

Analysis of Load Data

This section of the report summarizes findings from our analysis of PG&E's customer load data, including analysis of load changes by RTEM customers, and the extent to which those load changes may have been affected by their use of the InterAct website information. We begin by summarizing the energy prices faced by the customers who received the RTEM equipment, and providing illustrative data on typical load profiles by various customer groups. We then describe the regression analysis methods used and the resulting estimates of customer price response.

TOU Prices

The prices faced by the A10 and E19 rate classes are shown in Table 6.1. The first two sets of columns show the A10 rates prior to and after conversion to TOU energy prices for those customers receiving RTEM meters.

Table 6.1 A10 and E19 Energy and Demand Charges

	A10		A10 TOU		E19	
	Summer	Winter	Summer	Winter	Summer	Winter
Demand charges ($/kW)						
All hours					$ 2.55	$ 2.55
Seasonal	$ 6.70	$ 1.65	$ 6.70	$ 1.65		
On-peak					$ 13.35	
Mid-peak					$ 3.70	$ 3.65
Non-TOU energy charges ($/kWh)						
	$ 0.160	$ 0.112				
TOU energy charges ($/kWh)						
On-peak (Hrs 13 - 18)			$ 0.195		$ 0.188	
Mid-peak (8:30 - 12; 6 - 9:30)			$ 0.152	$ 0.115	$ 0.109	$ 0.115
Off-peak			$ 0.144	$ 0.108	$ 0.092	$ 0.092

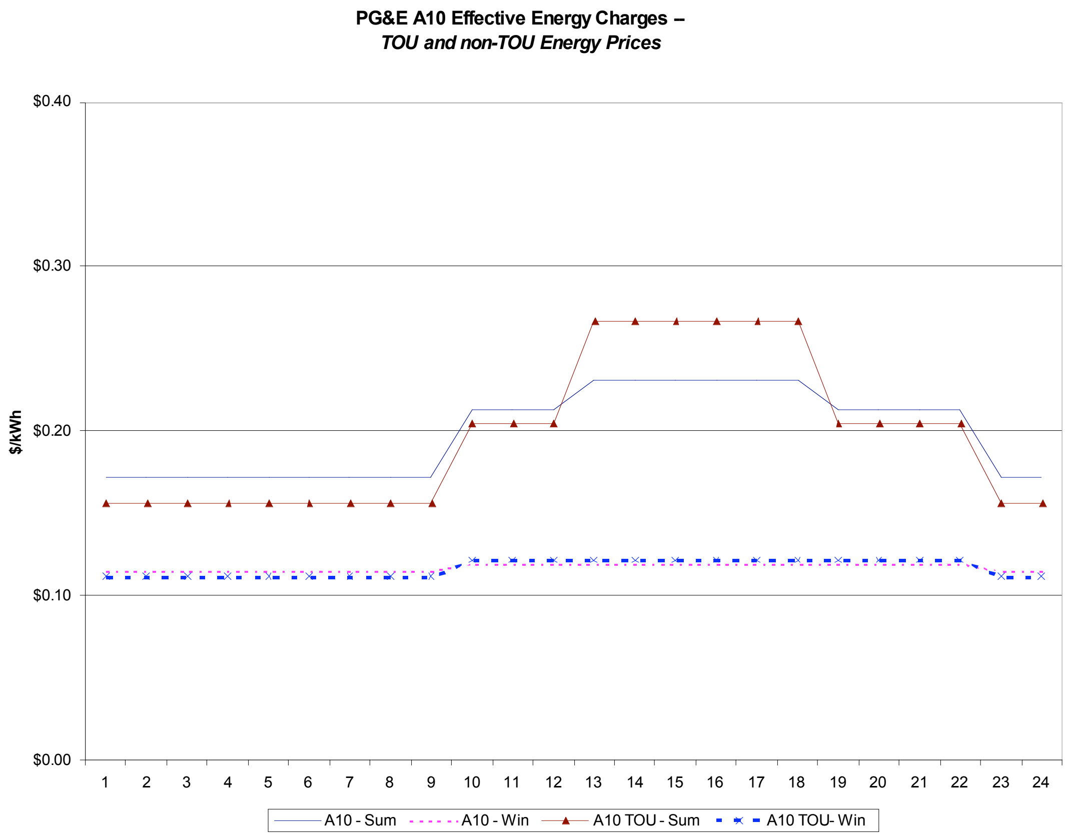
Several observations may be made about the prices faced by the A10 and E19 customers, both before and after they received RTEM equipment:

- Both groups faced substantial price signals that electricity was more costly during the summer (A10) and/or summer peak periods (E19). Even though the A10 customers did not face explicit TOU energy prices while on the non-TOU rate, to the extent that their typical usage pattern involved higher loads during the afternoon hours, the seasonal demand charge implied that their effective cost of electricity was higher during those hours. This is the case because any increase in hourly usage during that period has some chance of setting a higher billing demand and thus incurring an additional demand charge (see Figure 6.1 below).
- The new A10 TOU energy charges had relatively modest summer peak/off-peak and peak/mid-peak differentials of approximately 1.3 to 1, and a ratio of the new peak energy price to the previous A10 summer energy charge of less than that. These values suggest a relatively modest change in the effective price of electricity in the different TOU periods, as illustrated in Figure 6.1 below.
- In contrast, the E19 on-peak price signal was much stronger, with a peak/off-peak energy price ratio of nearly 2 to 1, plus a large summer peak demand charge. This price signal already existed prior to installation of the RTEM equipment.

Finally, the only price *change* over the time period for which customer load data were available was the effective price increase that each customer saw during the summer months (which PG&E's tariffs define as May through October), particularly in the peak afternoon hours, relative to the same period in the non-summer months. This price signal was substantially stronger for the E19 customers than for the A10 customers.

For purposes of understanding the price incentives inherent in utility tariffs that contain both demand and energy charges, we find it useful to combine the charges into a single measure of customers' *effective energy charge* (EEC) during particular time periods. The EEC indicates the change in a customer's monthly bill for a unit change in hourly consumption in a particular time period. The EEC effectively allocates demand charges over hours in proportion to the likelihood

Figure 6.1 A10 Effective Energy Charges

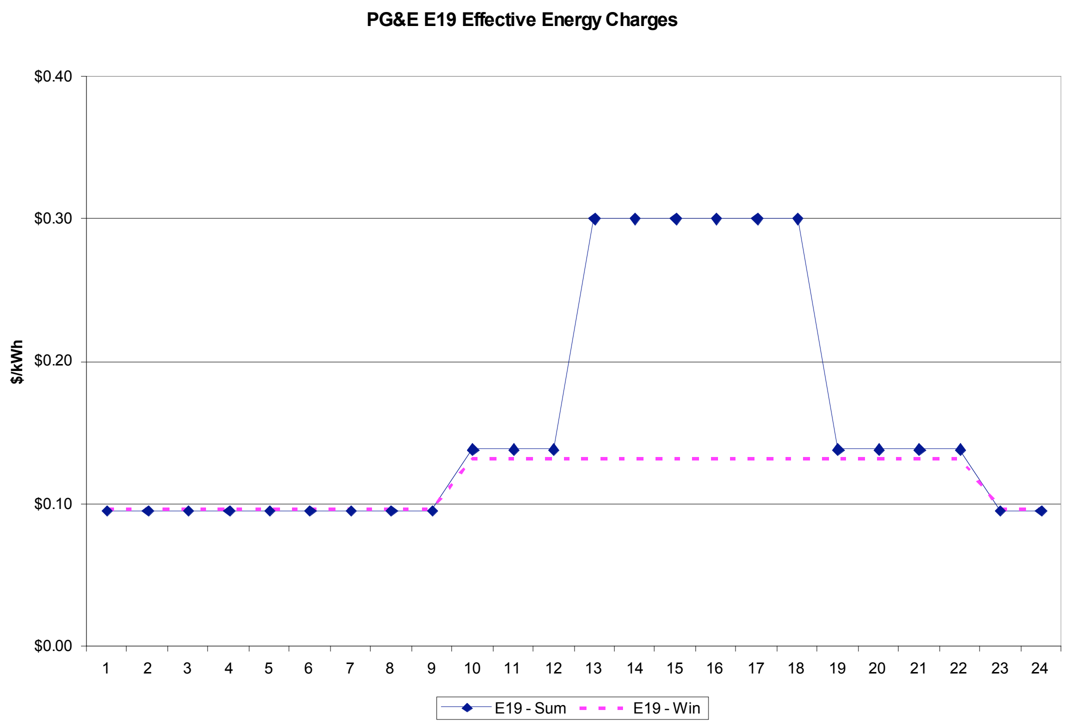


of incurring an additional demand charge in those hours. For example, if a peak demand charge applies in 126 hours of a month (6 hours on each of 21 weekdays), and a customer perceives that it is equally likely of setting a new billing demand in any of those hours, then the demand charge may be allocated equally across all of those hours (*e.g.*, for the E19 rate, the $13.35/kW demand charge would be allocated by a charge of $.106/kWh to each peak period hour). The allocated demand charge may then be combined with the energy charge to produce an estimate of the customer's effective cost per kWh in each peak hour. Figures 6.1 and 6.2 illustrate EECs for the A10 (with and without the TOU energy prices) and E19 tariffs respectively, for the summer and non-summer months. Note in particular that the EEC during the peak period defined by the summer prices is much higher during the summer than non-summer months for both tariffs, while the change to TOU energy prices had only a modest effect on A10 customers' summer peak EEC.

Potential Bill Savings From TOU Load Response

We can also calculate the incentive that PG&E's commercial and industrial customers had to reduce summer peak-period usage in 2002 and 2003. Specifically, using the A10 and E19 tariffs, and a typical consumer's load profile, we calculate 1) the annual bill for an example customer in each rate class, and 2) the effect on that bill of reducing load during the summer peak period by

Figure 6.2 E19 Effective Energy Charges



particular amounts. Table 6.2 summarizes these bill savings examples. For example, a 400 kW A10 customer would face an annual bill of more than $300,000, but could reduce that bill by amounts ranging from less than 1 percent to more than 3 percent by reducing load in the summer peak period (including maximum demand) by 2 to 15 percent. These bill savings would range from less than $1,500 to about $10,000 per year.

Table 6.2 Bill Savings From Summer Peak Load Reductions

Rate class	Max kW	Annual bill ($000)	% Bill savings at given peak load reduction			
			2%	5%	10%	15%
A10	400	$ 311.9	0.44%	1.1%	2.2%	3.3%
E19	800	$ 558.7	0.63%	1.6%	3.2%	4.7%

Similarly, an 800 kW E19 customer facing an annual bill of about $560,000 could save from 0.6 to nearly 5 percent of annual electricity costs by the same percentage peak-period load reductions, amounting to bill savings of $3,500 to $26,000.

Aggregate Load Profiles

Before presenting results of our analysis of customer price response, we first provide a picture of the load data for several different customer groups and for different time periods. The following figures illustrate aggregate load data for several different groups of interest. The load data for individual customer accounts were first divided into groups based on *rate class* (A10 and E19) and then by one-digit SIC code. The following listing indicates the types of businesses typically included in each of the SIC categories:

- SIC 2 – Manufacturing, including Food; Lumber and Wood Products; Paper; Printing; Chemicals; and Petroleum products.
- SIC 3 – Manufacturing, including Rubber and plastics; Stone, clay and glass; Primary and Fabricated metal; and various Equipment and Assembly industries.
- SIC 4 – Transportation and public utilities, including Warehousing; Water transportation facilities; Pipelines; Communications; and Water supply and Sewage systems.
- SIC 5 – Wholesale and Retail trade, including Wholesale durable and non-durable goods; and Retail department and food stores, restaurants, and other stores.
- SIC 6 – Finance, insurance and real estate, including financial institutions and office buildings.
- SIC 7 – Services, including hotels; business services; auto and other repair services; and entertainment facilities.

The figures below represent average hourly loads across customer accounts in each group, and then across hours defined by the summer TOU pricing period for weekdays in the following months in 2002 and 2003:[9]

- April, representing a period closest to when the summer TOU prices take effect, but when non-summer prices apply, and
- May, representing weather conditions similar to April, but within the summer TOU pricing period of May through October.

For purposes of interpreting differences in average loads between the key comparison months of April and May, Figure 6.3 illustrates the customer-weighted CDDs for those months in both years. The bars indicate that usage in May likely contains more cooling load than usage in April, and that this difference is likely more pronounced in 2003 than in 2002.

Figures 6.4 a-e and 6.5 a-e show average weekday TOU time-period load profiles for April and May for the indicated customer groups, for both 2002 and 2003. In each case, the loads for April are shown as dashed lines and those for May in solid lines, and the loads in 2003 are shown in bolder lines without indicators for individual hourly values. The following observations may be made about these figures:[10]

[9] Each hour in the straight-line load profiles was assigned the average hourly load that was measured across all hours in the TOU time period.

[10] We confined our analysis to customer accounts in SIC groups 2 through 7. We excluded accounts in SIC 8 due to the large number schools in that category, which have definite summer schedules that would make it difficult for our analysis approach to identify price responsive behavior. We excluded accounts in SIC 9 due to the presence of military bases and other unique government facilities.

Figure 6.3 Monthly Cooling Degree Days (Weekdays) –
April and May, 2002 and 2003

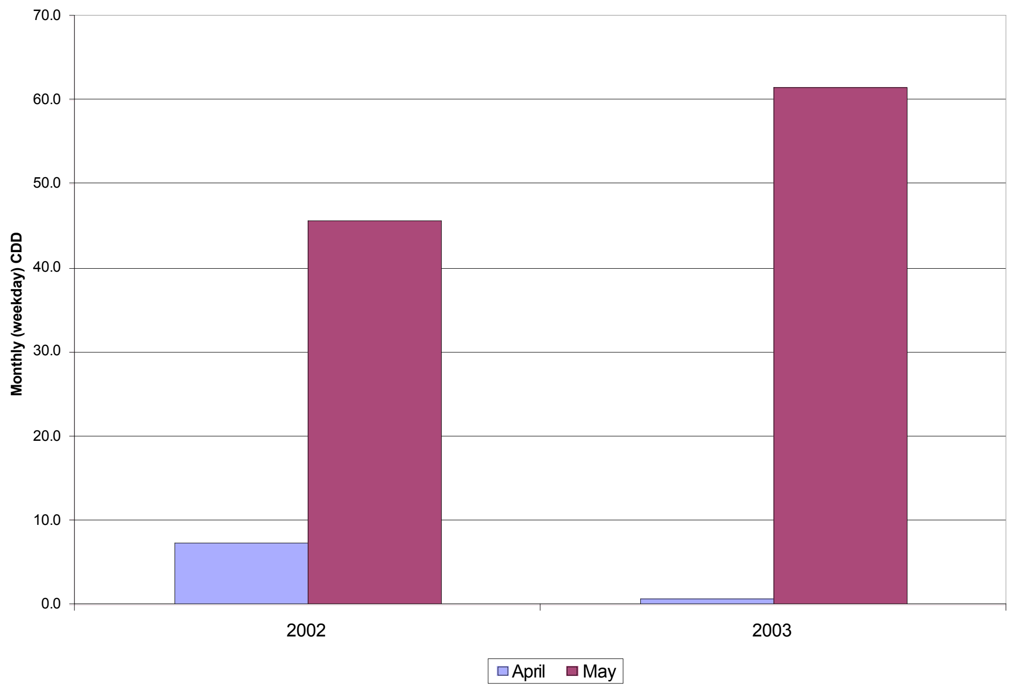
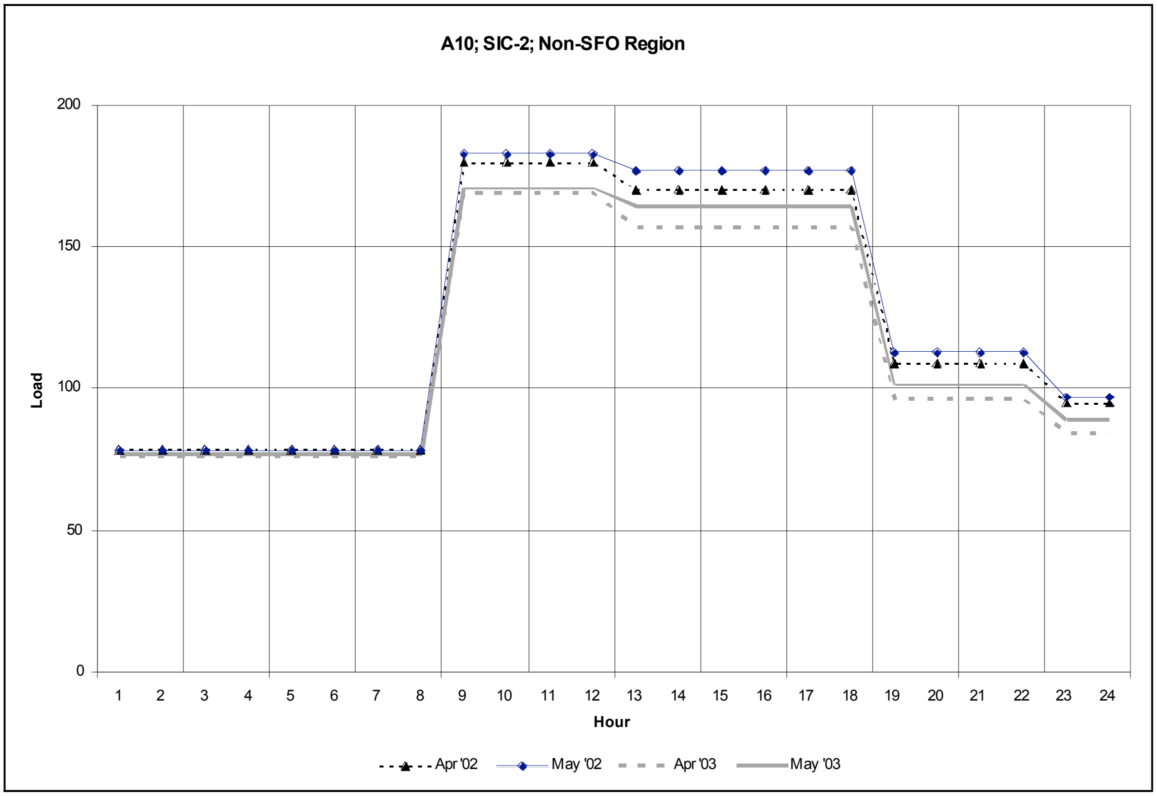
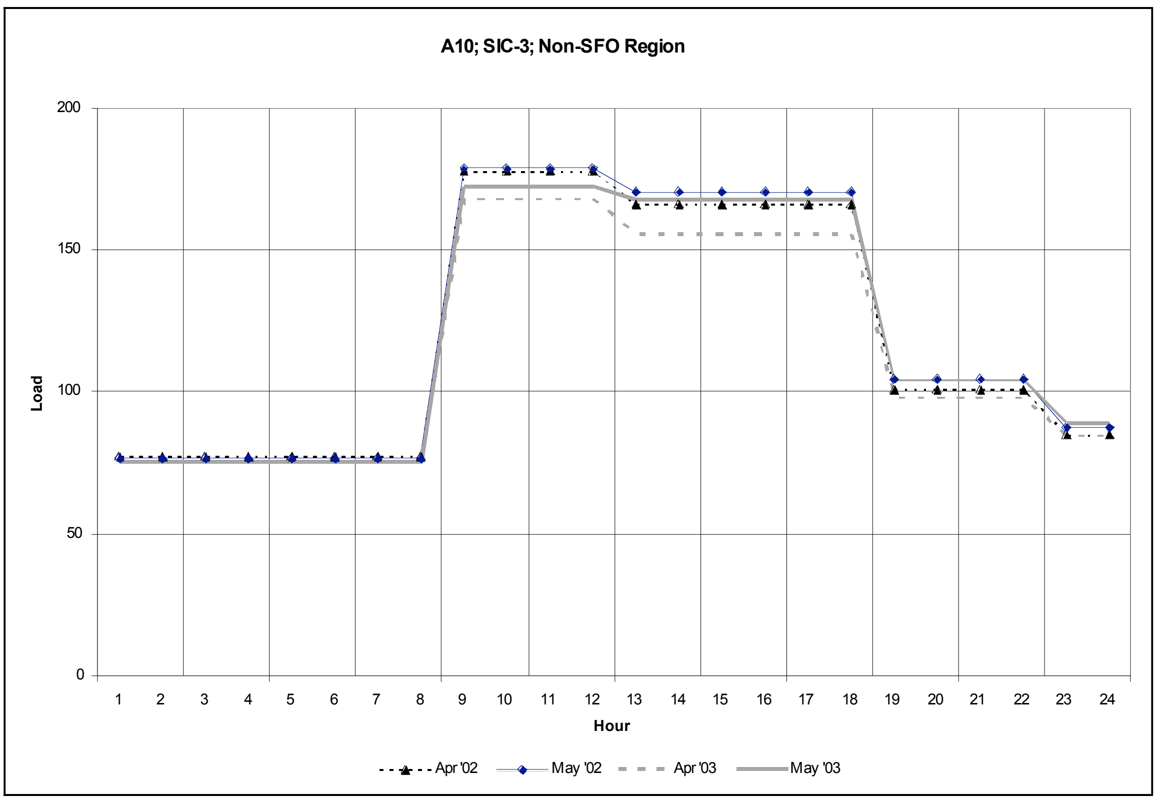
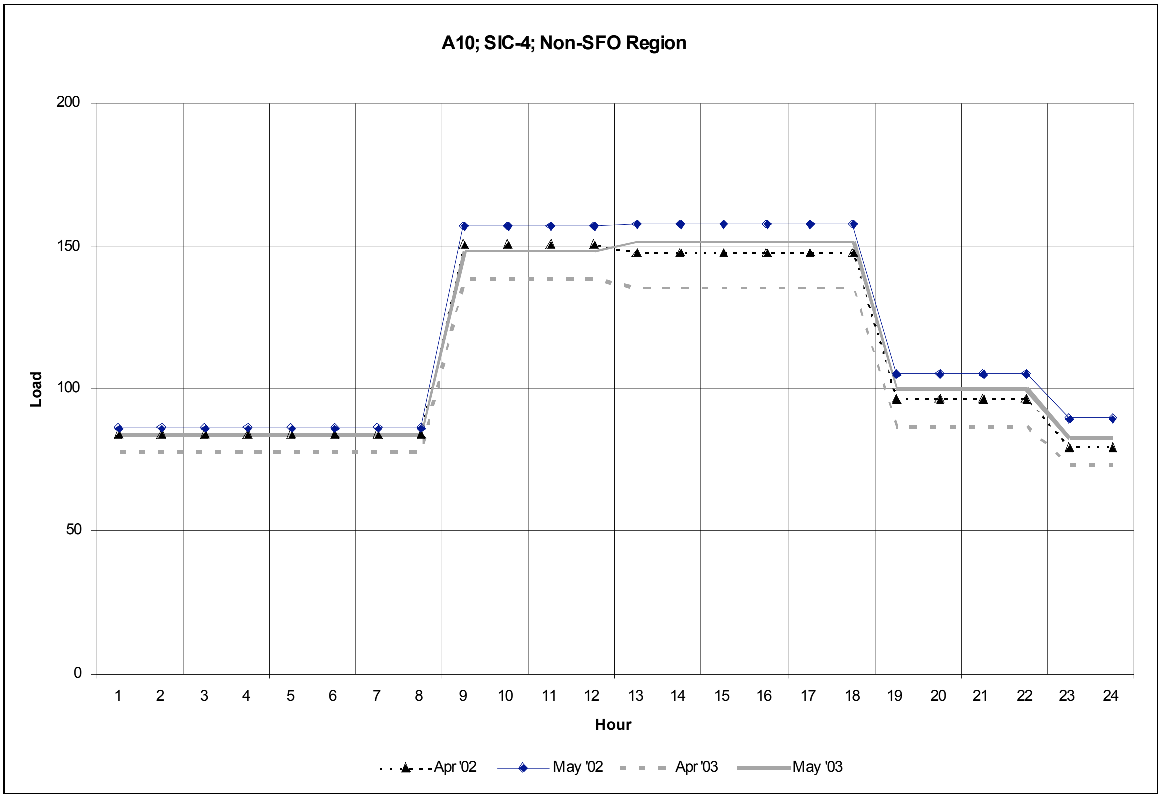
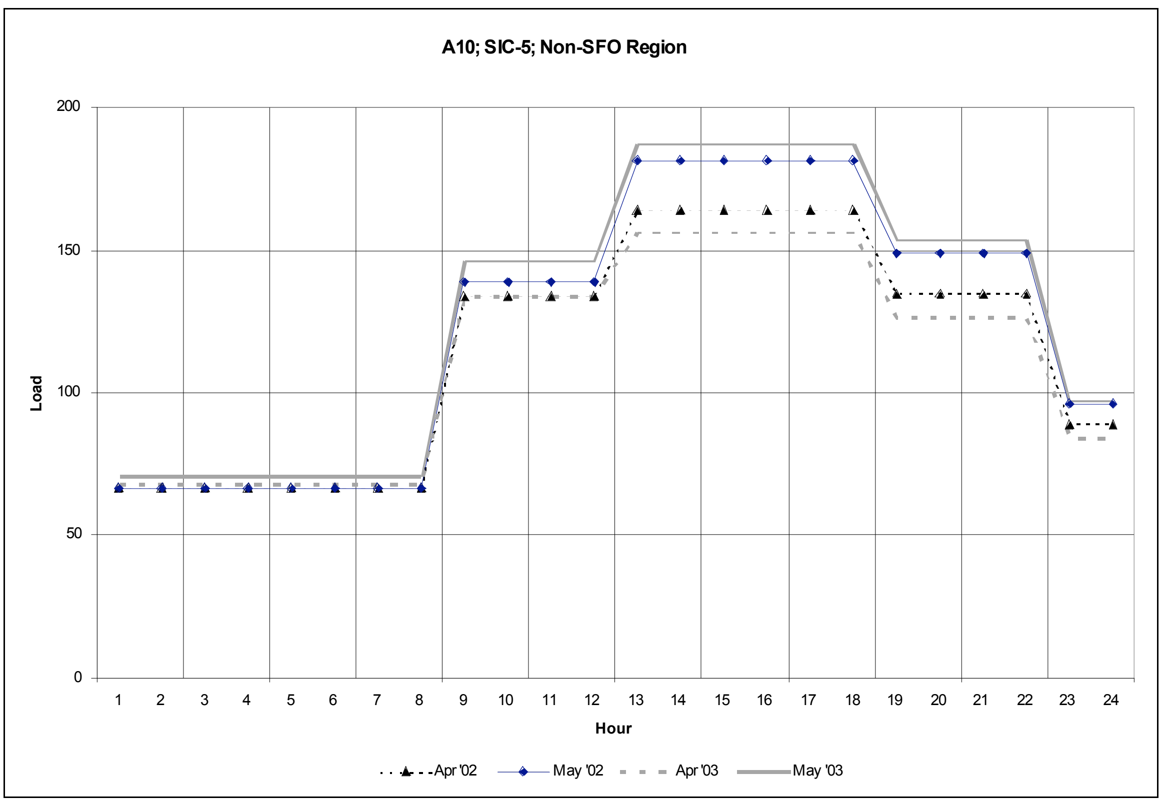


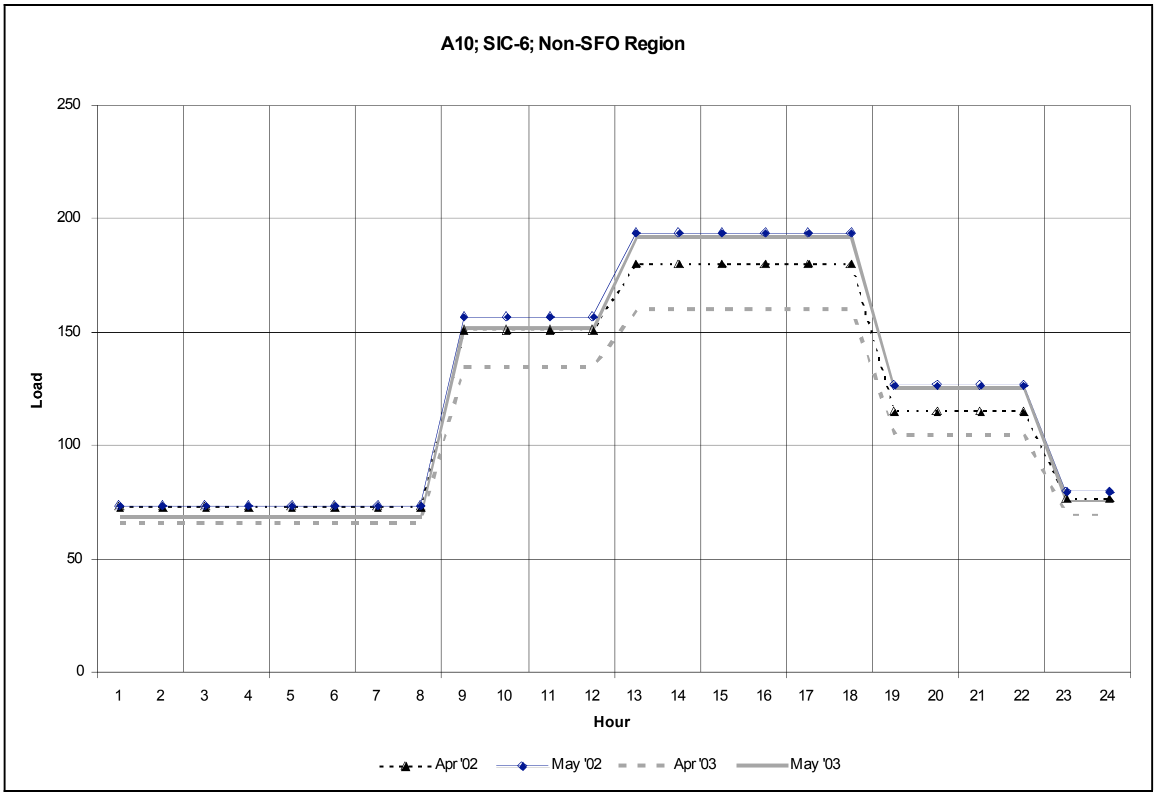
Figure 6.4 a - e A10 Aggregate Loads by SIC Group






A10; SIC-4; Non-SFO Region
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03


A10; SIC-5; Non-SFO Region
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03


A10; SIC-6; Non-SFO Region
250
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03

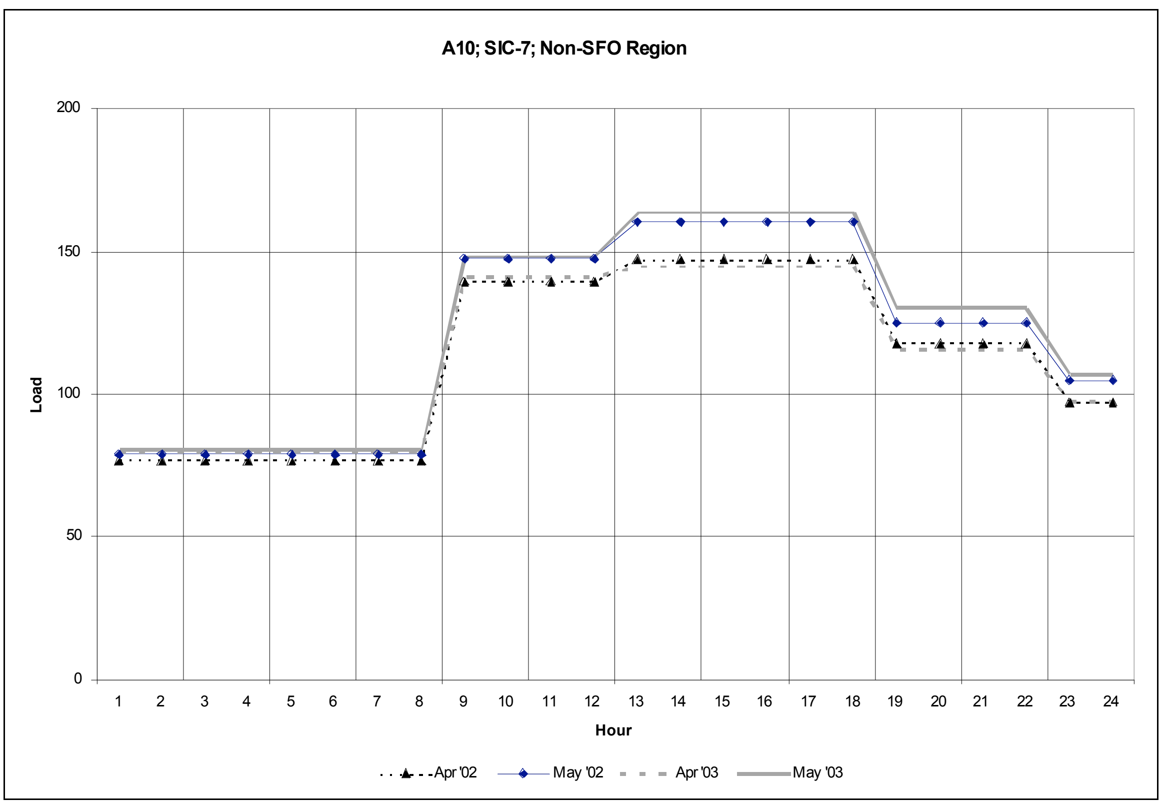
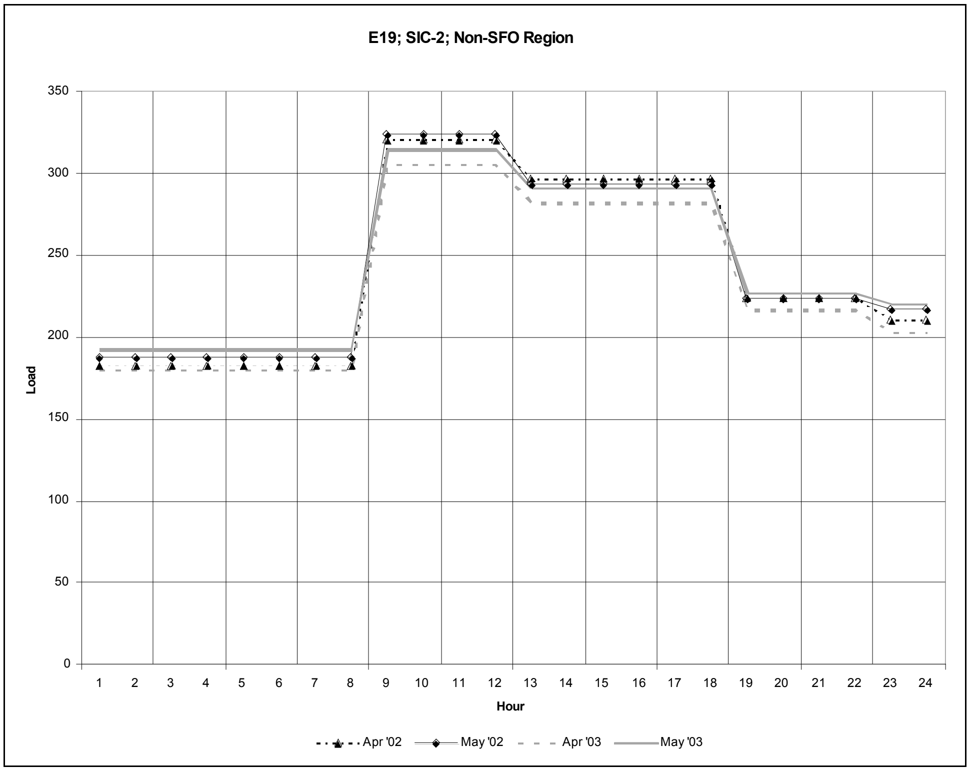
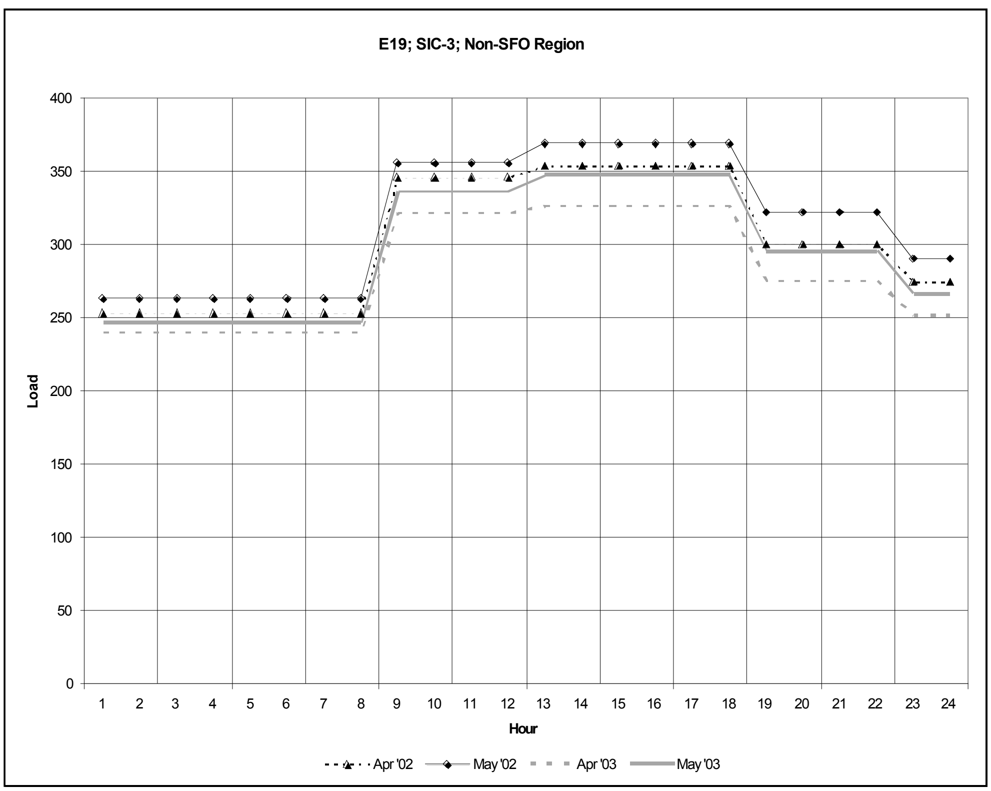
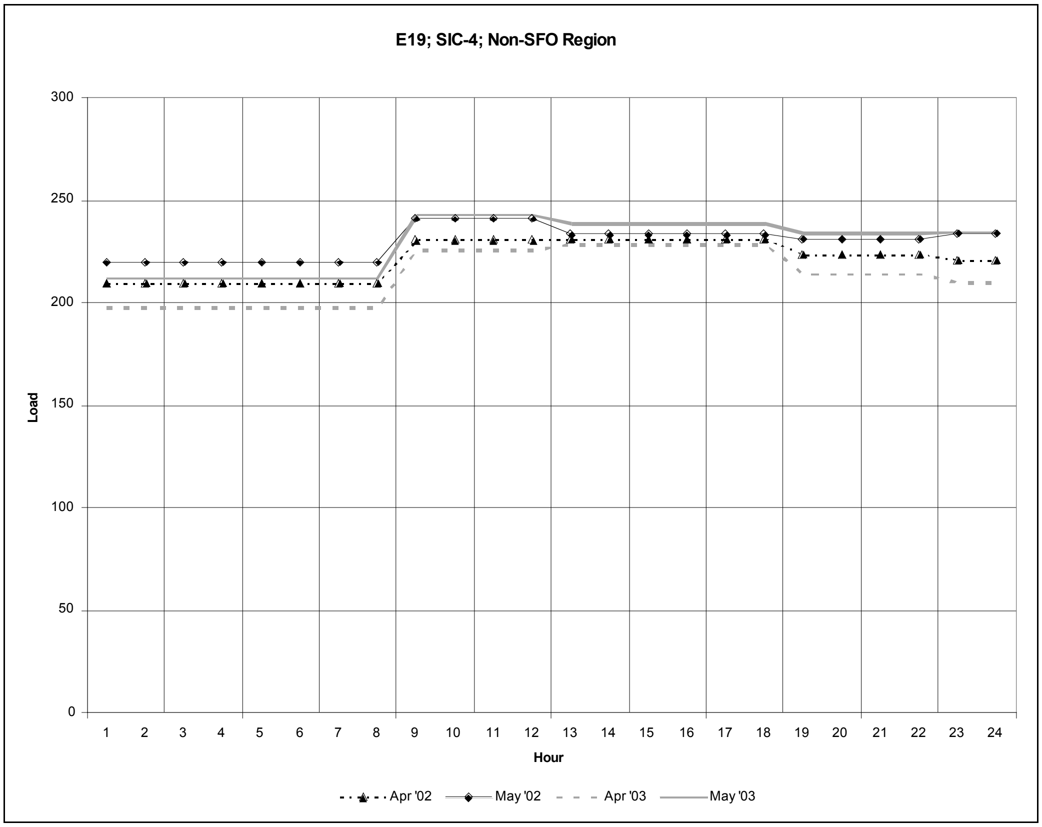
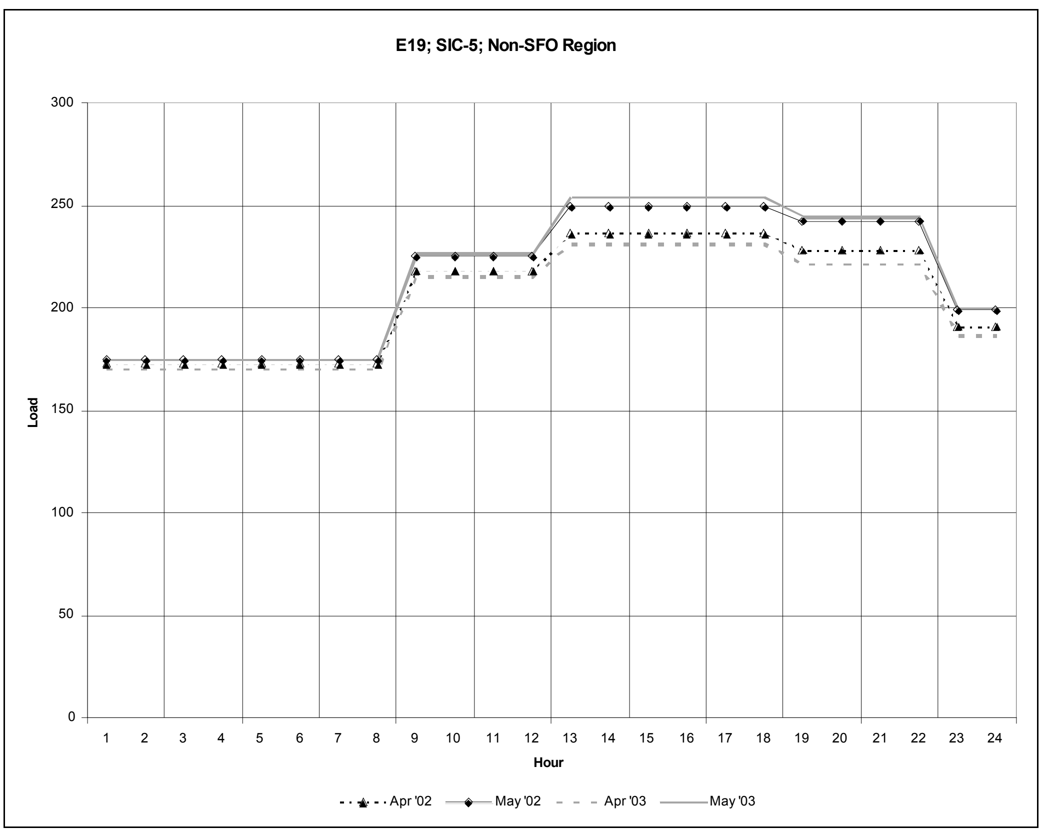

A10; SIC-7; Non-SFO Region
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03

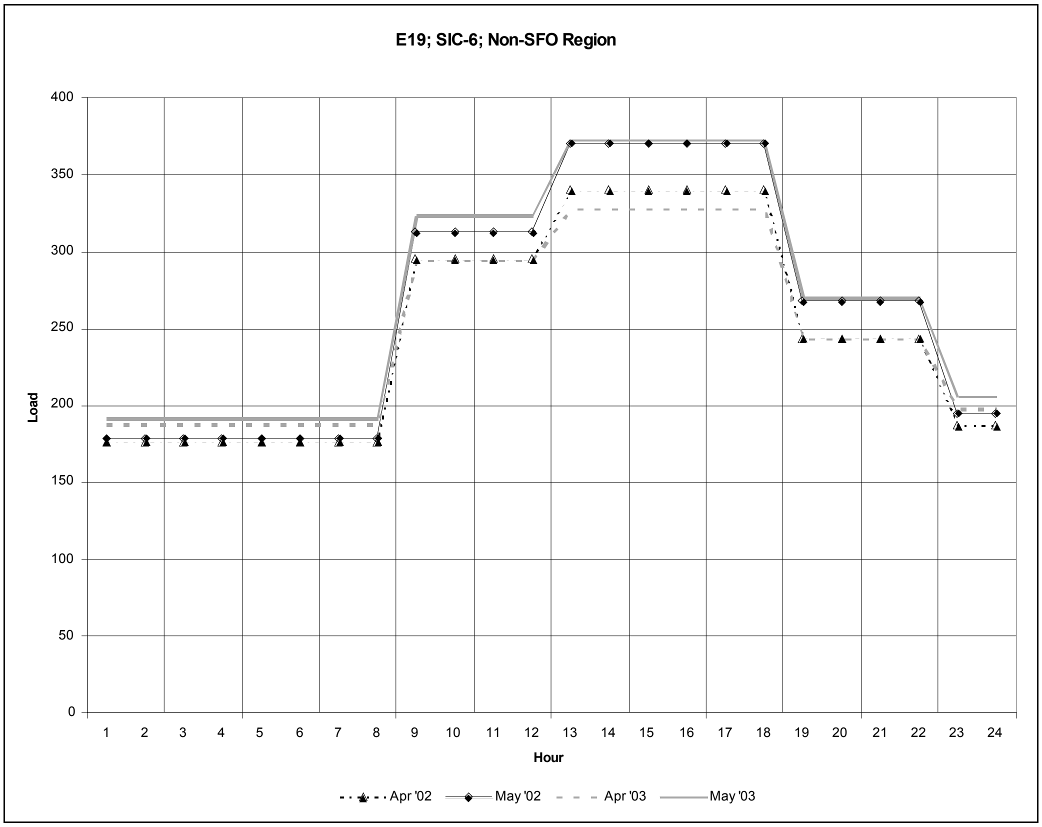
Figure 6.5 a - e. E19 Aggregate Loads by SIC Group

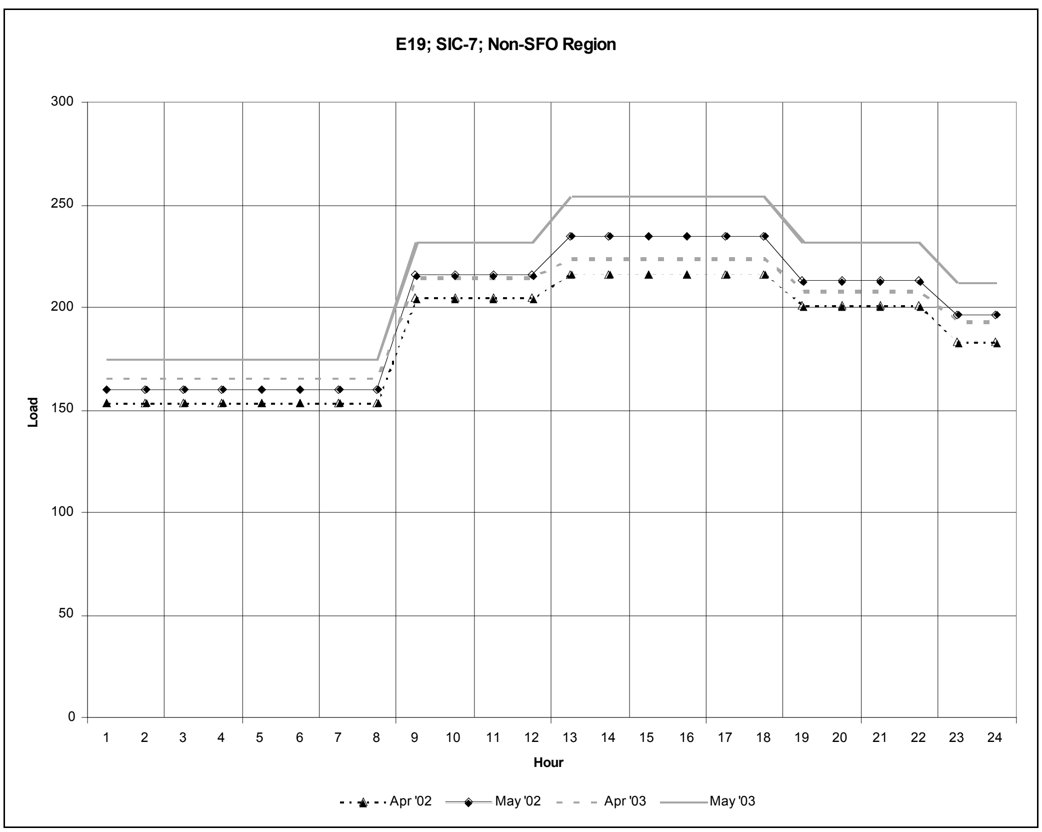





E19; SIC-4; Non-SFO Region
300
250
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03


E19; SIC-5; Non-SFO Region
300
250
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03


E19; SIC-6; Non-SFO Region
400
350
300
250
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03


E19; SIC-7; Non-SFO Region
300
250
200
150
100
50
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03

Analysis Approach

As was the case for SCE, the only *price change*, or difference that we can observe for either rate class is for the change from non-summer months to the summer months of May through October, for which the demand and TOU energy prices were higher. Thus, we applied an analysis approach that was designed to measure differences in energy usage during, for example, the summer peak time period relative to the same time period in non-summer months, after controlling for the effect of weather and other variables that might be expected to affect consumption. We interpreted significant measured reductions in summer peak-period usage levels or shares, after controlling for weather, as indicative of TOU price responsive behavior.

We used regression analysis to implement the above analysis approach, using some variables designed to control for factors such as weather conditions that would be expected to affect daily changes in energy usage, and others designed to indicate time periods such as the summer months, and time periods during those months for which prices differed. We conducted two levels of analysis, using daily observations on electricity use by TOU time period, for the period from the spring of 2002 to December 2003. The analyses included the following:

- *Pooled analysis* using individual customer account data within one-digit SIC groups (*e.g.*, SIC 2 consisted of hourly loads for all customer accounts in SIC codes 20–29) for each rate class, thus resulting in separate estimates of parameters by SIC group that represent averages across customers in each group.
- *Individual customer-level analysis*, resulting in separate estimates of price response parameters for each customer account, and an ability to examine the distribution of such parameters across customer accounts in each group.

For PG&E customers, our analysis closely followed the approach developed for SCE customers. However, several important factors distinguish it:

1. PG&E provided electricity use data for several thousand commercial and industrial customers. The higher number of customers permitted greater flexibility in our analysis approach, including the following strategies:
   - homogenize weather periods using month restrictions;
   - analyze groups of relatively homogenous customers by grouping customers at the one-digit SIC level;
   - employ regional analysis by separating weather zones.
2. PG&E provided relatively limited information on customer use of software for monitoring electricity use (referred to as Interact software).

These topics are discussed in greater detail below.

Regression Framework

We used regression analysis to attempt to isolate TOU price response and program effects from the impact of weather. The underlying regression equation was,

$$ln(E_{it}^{T}) = \boldsymbol{B}\, \boldsymbol{X}_{it} + \boldsymbol{D1\ Year} + \boldsymbol{D2\ Year * Summer} + v_i + e_{it}.$$

E_{it} represents electricity usage for customer i on day t, T denotes one of five time periods defined by PG&E's summer TOU prices, $\boldsymbol{X}_{it}$ are quadratics of HDD and CDD to control for nonlinear effects of weather, ***Summer*** is a dummy variable corresponding to PG&E's Summer pricing period (May – October), and ***Year*** represents dummy variables for the years included in the analysis. The error term is decomposed into two components: v_i and e_{it}, where v_i represents unobserved customer-specific characteristics that do not change with time, and e_{it} is the traditional error term, assumed to have a mean of zero and be normally distributed. The customer-specific component of the error, v_i, was captured in the model using customer fixed effects.

The model was used to estimate the coefficients denoted ***B***, ***D1***, and ***D2***. Regression results from applying the model to all (or a group of) customers at once are referred to as *pooled* results. The same underlying model was also applied to customers individually, providing customer-specific estimates of the coefficients. These results are referred to as *individual customer* results.

As in our approach with SCE, the equation presented above was estimated for three different measures of electricity usage. The first measure was *total daily use*, where a monthly time trend was included in the model to account for systematic but otherwise unexplained changes in the trend of usage. The second measure was *average daily use* within each of the following five *time periods* defined by PG&E's tariffs for summer:

- a.m. summer off-peak period,
- a.m. shoulder period,
- peak pricing period,
- p.m. shoulder period, and
- p.m. off-peak period.

The third measure was the *share of daily use* in each time period. That is, for each customer, we calculated $kWh_{it}^{T}/\Sigma_{T}kWh_{it}^{T}$, for T = 1, 2,…,5.

In all, 11 separate regressions were estimated at the 1 digit SIC level. To further homogenize weather patterns and isolate weather-usage relationships, the regression framework was applied separately to two aggregate weather zones, producing separate estimates for PG&E customers in the San Francisco (SFO) weather zone, and for customers elsewhere in the PG&E service territory.

PG&E's Summer pricing period extends from the beginning of May through the end of October. Consequently, there was relatively little weather similarity between the Summer and non-summer pricing periods. That is, in the case of SCE, one could imagine some days of similar weather in May and June, thus allowing the regression analysis to isolate the effect of the higher peak TOU demand and energy charges in June relative to May. However, in the case of PG&E,

one would expect few days of cooling in April, implying that differences in usage by time period in April and the summer months would be affected by both weather and the price differences. In an attempt to homogenize Summer and non-summer day types, we conducted a restricted regression analysis using observations only in April, May, June, and October. The goal of this approach of basing the weather relationship on days as similar to one another as possible was to mitigate the extent to which the summer pricing period variables might overwhelmingly capture usage changes caused by especially hot mid-Summer weather periods. With this restriction, April served as the only non-summer month by which to measure differences between the summer and non-summer periods.

Direct access customers who purchase energy from a provider other than PG&E were omitted from the analysis, as were customers who changed between major tariff groups at any point in the analysis period, such as switching to an E19 tariff from an A10 tariff. In addition, only customers in SIC 2 through SIC 7 were included in this analysis (SIC 8 was excluded due to the large number of schools with their different summer schedules). These screens affected the number of customer accounts included in the analysis. Within these parameters, additional sample restrictions included focusing the analysis on non-holiday weekdays and scrubbing observations for zero values and missing hourly observations. These latter screens affected the number of observations included.

Interpreting Results

Recall that by transforming electricity use into its natural logarithm, represented by *ln()*, the estimated coefficients may be interpreted as percentage changes. For example, a coefficient of 0.02 on the CDD variable implies that a 10 unit increase in CDD leads to a 20 percent increase in energy usage (10 * 0.02 * 100% = 20%). For dummy, or shift variables, such as the variable for Summer 2003, the coefficient represents the *percentage change* in usage during the period *relative to a particular comparison period*. For instance, a coefficient on that variable equal to -0.3 in the equation for the peak time period implies that peak-period energy usage was 30 percent lower during the Summer pricing period of 2003 *relative to the rest of 2003*, after controlling for weather differences. The year-summer interactions measure the conditional difference in electricity use relative to the level in that year. Due to the natural log transformation of the dependent variable, the coefficients are scaled implicitly so that relatively large or small customers do not have an undue influence on results.

Quadratic weather variables refer to the inclusion of two variables each for CDD and HDD. The two variables are the original variable and its squared value. Separate coefficients are estimated for each variable. The quadratic formulation of weather permits the regression to estimate a non-linear relationship between weather and electricity consumption[11]. However, to get the total effect on usage changes caused by changes in weather, both terms must be considered. For example, suppose the following values were estimated for the CDD terms:

$0.014 * CDD - 0.001 * CDD^2$.

To obtain the total effect, we plug in a change for the CDD value in *both* terms. In this case, a one-unit increase in CDD would lead to the following change in electricity use: 0.014 * 1 - 0.001

[11] Nonlinear relationships can be estimated in several ways, including using shift variables and interactions. A quadratic is one particular form of a nonlinear relationship.

* 1^2 = 0.013, or an increase of 1.3%. With an increase in CDD equal to two, electricity use increases by 0.014 * 2 - 0.001 * 2^2 = 0.024, or 2.4%.

Econometric Analysis—Results

The approach outlined above leads to a series of regressions that were estimated at a variety of levels, including pooled across all customers, pooled by SIC categories, and at the customer level.

Pooled Estimation

PG&E pooled regression results are presented in Tables 6.3 through 6.5. Coefficients and t statistics are presented for weather and summer pricing period variables for three of the eleven regressions estimated for each SIC-weather zone classification. The three regressions correspond to *total daily use*, the *period three (peak) usage level*, and the *period 3 usage share*. Results in Table 6.3 include those for A10 customers for both the SFO weather zone and elsewhere in PG&E's service territory. Table 6.4 gives similar results for E19 customers. Table 6.5 presents results for E20 customers, which were not separated by weather zone.

Coefficients and t-statistics are presented for weather variables and for summer-year interactions, where summer corresponds to PGE's summer pricing period. We focus on the peak pricing period (the hours between noon and 6:00 p.m.) because it represents the period that has the greatest price difference between seasons—and therefore represents the strongest price signal to customers. Economic theory suggests that consumers will use relatively less in high-price periods, all else equal.

Weather effects. For most A10 SIC groups, the coefficients on CDD indicate that customers use significantly more electricity on days of higher temperatures. For instance, in the Daily Use column for SIC 2, the CDD terms indicate that consumption increases substantially with number of CDDs, as shown by the positive coefficient on the linear CDD term. The negative coefficient on the squared term indicates that the positive effect diminishes with continued temperature increases. Recall that the dependent variable has been transformed into its natural logarithm, implying that the change may be stated as a percentage. In the latter case, the interpretation of the coefficient is that a 2 degree increase in the average daily temperature (implying a 2-unit increase in CDD) leads to an increase in electricity consumption of 2.4%. Since the t-statistic on both terms is greater than 1.96 in absolute value, the effect is statistically significant.

The CDD results for the SFO zone go as one would expect. Typically, customers use more electricity on hotter days, both overall and during the peak period. An exception is SIC 4 (which includes pipelines, and water and sewer utilities) and a few other cases, where the CDD coefficients are small or not statistically significant in one or both cases. In cases where the squared term is insignificant, a single linear measure of CDD would be sufficient for modeling the weather effect.

Also worth noting is the fact that the coefficients on linear HDD terms frequently are significantly negative. HDD increases as the average daily temperature falls. The negative coefficients therefore imply that customers are reducing electricity consumption with decreasing temperatures. This probably indicates that customers are not heating with electricity, perhaps because we are measuring effects during time periods that are largely outside of the heating

Table 6.3 Pooled Model Coefficient Estimates – A10 Customer Groups

A10 Customers	SFO Weather Zone						Non SFO Weather Zone					
	Peak Level		Daily Use		Peak Share		Peak Level		Daily Use		Peak Share	
SIC 2. Food/paper/chemicals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.020	4.02	0.013	2.98	0.007	3.51	0.006	1.85	0.007	2.56	0.003	2.89
CDD squared	-0.001	-3.45	-0.001	-2.16	-0.001	-4.19	0.000	-1.86	0.000	-2.30	0.000	-1.47
HDD	-0.007	-1.94	-0.005	-1.64	-0.002	-1.24	-0.014	-4.63	-0.008	-2.69	-0.003	-2.48
HDD squared	0.000	-0.24	0.000	0.16	0.000	-0.49	0.000	1.42	0.000	-0.24	0.000	1.12
Summer * 2002	0.001	0.10	-0.029	-2.56	-0.008	-1.84	0.031	2.18	-0.040	-2.68	**-0.011**	**-2.31**
Summer * 2003	-0.006	-0.44	-0.028	-2.41	0.008	1.62	0.053	3.23	-0.022	-1.36	0.005	0.94
SIC 3. Plastic/stone/metals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.025	4.64	0.018	3.76	0.008	4.65	0.007	3.40	0.005	2.56	0.003	3.38
CDD squared	-0.001	-3.66	-0.001	-2.58	-0.001	-4.60	0.000	-0.79	0.000	0.06	0.000	-1.91
HDD	-0.007	-1.83	-0.003	-1.06	-0.004	-3.20	-0.014	-6.21	-0.010	-4.73	-0.005	-5.33
HDD squared	0.000	0.13	0.000	-0.13	0.000	0.42	0.000	1.94	0.000	3.14	0.000	1.15
Summer * 2002	-0.014	-1.19	0.015	1.26	0.002	0.64	**-0.030**	**-2.94**	-0.007	-0.72	**-0.027**	**-5.98**
Summer * 2003	0.024	1.74	0.019	1.48	0.016	3.81	0.003	0.25	-0.010	-0.93	-0.004	-0.87
SIC 4. Utilities/water supply	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.000	-0.03	0.003	0.24	-0.005	-0.61	0.015	2.87	0.013	3.01	0.003	1.06
CDD squared	0.000	0.16	0.000	-0.11	0.000	0.79	0.000	0.06	0.000	-0.42	0.000	0.50
HDD	-0.005	-0.50	0.013	1.24	-0.010	-1.83	-0.019	-3.72	-0.011	-2.52	-0.007	-2.60
HDD squared	0.000	-0.02	-0.001	-1.53	0.000	1.00	0.000	0.69	0.000	-0.51	0.000	1.81
Summer * 2002	-0.012	-0.37	0.081	2.02	0.032	1.75	0.025	1.06	0.004	0.19	-0.004	-0.29
Summer * 2003	**-0.147**	**-4.00**	-0.045	-1.12	**-0.052**	**-2.57**	0.110	4.00	0.089	3.56	-0.002	-0.10
SIC 5. Retail	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.007	1.64	0.006	2.09	0.001	0.57	0.013	10.84	0.011	11.33	0.002	4.17
CDD squared	0.000	-0.28	0.000	0.10	0.000	-0.96	0.000	-0.04	0.000	1.75	0.000	-3.07
HDD	-0.011	-4.04	-0.008	-3.98	-0.003	-1.78	-0.026	-19.71	-0.020	-19.20	-0.006	-9.15
HDD squared	0.000	-0.30	0.000	-0.19	0.000	-0.43	0.001	9.74	0.001	10.22	0.000	3.30
Summer * 2002	0.026	2.96	0.029	3.82	0.002	0.48	0.048	8.15	0.037	7.00	0.008	2.70
Summer * 2003	0.028	2.69	0.020	2.46	0.012	2.03	0.074	11.19	0.049	8.78	0.021	6.70
SIC 6. Office buildings	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.017	11.80	0.015	12.32	0.002	2.33	0.019	18.21	0.015	16.00	0.002	5.79
CDD squared	0.000	-4.78	0.000	-4.02	0.000	-2.32	0.000	-3.00	0.000	0.23	0.000	-7.16
HDD	-0.020	-21.01	-0.017	-19.91	-0.004	-8.52	-0.022	-19.15	-0.018	-16.80	-0.006	-15.64
HDD squared	0.000	-0.59	0.000	2.13	0.000	-6.33	0.000	4.13	0.000	4.51	0.000	3.62
Summer * 2002	-0.002	-0.53	0.025	7.49	0.010	6.55	**-0.011**	**-1.95**	0.020	3.57	-0.001	-0.48
Summer * 2003	0.021	5.94	0.032	10.31	0.002	1.49	0.025	4.71	0.039	7.35	0.011	6.32
SIC 7. Services	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.013	2.73	0.004	0.77	0.005	3.00	0.006	1.83	0.003	0.84	0.005	4.48
CDD squared	0.000	-0.83	0.000	0.75	0.000	-2.78	0.000	-0.51	0.000	0.82	0.000	-4.29
HDD	-0.013	-4.08	-0.010	-2.41	-0.003	-2.89	-0.028	-7.64	-0.019	-5.75	-0.008	-6.14
HDD squared	0.000	1.17	0.000	0.82	0.000	-0.60	0.002	5.91	0.001	5.27	0.000	2.59
Summer * 2002	-0.005	-0.47	0.041	2.70	0.013	3.42	0.129	7.92	0.096	5.81	0.003	0.56
Summer * 2003	0.029	2.36	0.059	3.76	0.011	2.47	0.009	0.49	-0.006	-0.33	-0.011	-1.68

Table 6.4 Pooled Model Coefficient Estimates – E19 Customer Groups

E19 Customers	SFO Weather Zone						Non SFO Weather Zone					
	Peak Level		Daily Use		Peak Share		Peak Level		Daily Use		Peak Share	
SIC 2. Food/paper/chemicals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.008	1.57	0.005	1.04	0.003	1.66	-0.003	-1.18	0.005	2.02	0.003	2.66
CDD squared	-0.001	-1.66	0.000	-0.49	0.000	-3.16	0.000	-0.37	0.000	-1.16	0.000	-3.08
HDD	-0.001	-0.40	0.000	-0.06	-0.001	-0.83	-0.016	-5.77	-0.007	-2.92	-0.004	-3.33
HDD squared	-0.001	-1.96	0.000	-1.92	0.000	-0.60	0.001	3.23	0.000	2.07	0.000	0.40
Summer * 2002	0.022	1.61	0.022	1.62	-0.002	-0.37	0.114	8.06	-0.031	-2.22	**-0.027**	**-4.16**
Summer * 2003	0.045	2.94	0.029	2.10	0.015	2.50	0.097	6.11	-0.009	-0.58	**-0.045**	**-6.10**
SIC 3. Plastic/stone/metals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.024	3.09	0.018	2.46	0.004	1.42	0.011	5.24	0.004	1.97	0.003	3.05
CDD squared	-0.001	-1.94	-0.001	-1.46	0.000	-0.83	0.000	-1.42	0.000	0.78	0.000	-2.73
HDD	-0.002	-0.27	0.000	-0.04	-0.003	-1.36	-0.017	-7.24	-0.014	-6.33	-0.007	-6.81
HDD squared	0.000	-1.10	0.000	-1.02	0.000	-0.45	0.001	3.77	0.001	3.65	0.000	3.98
Summer * 2002	0.000	0.00	0.106	5.07	**-0.048**	**-6.77**	**-0.033**	**-3.03**	0.058	5.23	**-0.031**	**-6.80**
Summer * 2003	0.028	1.21	0.073	3.36	**-0.022**	**-2.71**	**-0.069**	**-5.87**	0.011	0.92	**-0.027**	**-5.40**
SIC 4. Utilities/water supply	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	-0.004	-0.56	-0.004	-0.72	0.001	0.37	0.016	4.77	0.014	4.63	0.003	1.58
CDD squared	0.001	1.93	0.001	1.53	0.000	0.99	0.000	-0.09	0.000	-0.32	0.000	0.41
HDD	-0.018	-3.87	-0.015	-3.73	-0.003	-1.20	-0.012	-3.17	-0.014	-4.11	0.002	0.87
HDD squared	0.001	2.64	0.001	3.27	0.000	-0.17	0.000	0.47	0.001	2.33	0.000	-2.98
Summer * 2002	0.012	0.71	0.011	0.66	-0.013	-1.39	**-0.076**	**-4.00**	0.011	0.61	**-0.106**	**-9.40**
Summer * 2003	-0.011	-0.55	0.022	1.28	**-0.041**	**-3.95**	-0.010	-0.47	0.106	5.50	**-0.136**	**-10.76**
SIC 5. Retail	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.013	4.07	0.010	3.92	0.002	1.43	0.008	15.25	0.006	13.42	0.002	6.54
CDD squared	0.000	-1.92	0.000	-1.17	0.000	-1.51	0.000	-0.05	0.000	1.84	0.000	-2.83
HDD	-0.010	-4.38	-0.006	-3.47	-0.004	-3.77	-0.013	-22.94	-0.010	-19.11	-0.004	-12.42
HDD squared	0.000	-0.01	0.000	-0.98	0.000	1.56	0.001	13.53	0.000	10.74	0.000	8.20
Summer * 2002	0.036	4.58	0.050	7.10	0.005	1.35	0.014	4.98	0.014	5.12	0.000	-0.16
Summer * 2003	0.010	1.05	0.017	2.36	0.000	-0.05	0.023	7.02	0.020	6.43	0.003	2.03
SIC 6. Office buildings	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.015	7.62	0.013	7.58	0.000	-0.34	0.020	9.08	0.015	7.93	0.002	3.27
CDD squared	0.000	-2.74	0.000	-1.87	0.000	-0.33	-0.001	-3.89	0.000	-2.83	0.000	-2.63
HDD	-0.017	-11.97	-0.014	-10.85	-0.004	-8.03	-0.016	-6.51	-0.014	-6.91	-0.005	-6.61
HDD squared	0.000	-2.19	0.000	0.07	0.000	-5.69	0.000	-0.31	0.000	0.94	0.000	-0.40
Summer * 2002	0.004	0.70	0.030	5.31	0.012	5.62	0.031	2.33	0.071	6.07	0.003	0.79
Summer * 2003	0.005	0.92	0.014	2.87	0.006	2.90	0.016	1.40	0.046	4.41	0.009	2.68
SIC 7. Services	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.008	3.03	0.004	1.89	0.003	3.21	0.012	6.12	0.009	4.92	0.005	5.34
CDD squared	0.000	1.65	0.000	2.90	0.000	-1.53	0.000	-0.78	0.000	0.19	0.000	-3.32
HDD	-0.010	-4.96	-0.005	-3.26	-0.005	-7.22	-0.014	-5.93	-0.008	-3.37	-0.004	-3.42
HDD squared	0.000	0.93	0.000	0.70	0.000	1.05	0.000	1.24	0.000	0.63	0.000	-0.44
Summer * 2002	0.042	5.97	0.055	8.17	0.006	2.58	0.016	1.50	-0.006	-0.50	**-0.017**	**-3.74**
Summer * 2003	0.061	7.39	0.054	7.68	0.014	4.94	0.058	5.14	0.034	2.84	-0.007	-1.33

Table 6.5 Pooled Model Coefficient Estimates – E20 Customer Groups

E20 Customers	All Weather Zones					
	Peak Level		Daily Use		Peak Share	
SIC 2. Food/paper/chemicals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.001	0.41	0.004	1.58	0.001	0.84
CDD squared	0.000	-0.63	0.000	-1.67	0.000	0.16
HDD	-0.026	-8.08	-0.015	-5.59	-0.011	-5.52
HDD squared	0.002	8.83	0.001	5.92	0.001	6.85
Summer * 2001	**-0.040**	**-2.04**	0.006	0.33	**-0.126**	**-10.90**
Summer * 2002	**-0.049**	**-2.86**	0.006	0.36	**-0.143**	**-14.35**
Summer * 2003	-0.036	-1.84	-0.007	-0.43	**-0.096**	**-8.44**
SIC 3. Plastic/stone/metals	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.008	3.17	0.004	2.12	0.003	1.82
CDD squared	0.000	-1.75	0.000	-1.48	0.000	-0.61
HDD	-0.015	-5.71	-0.008	-3.73	-0.008	-4.64
HDD squared	0.001	5.05	0.000	3.00	0.001	4.42
Summer * 2001	**-0.156**	**-9.87**	0.002	0.14	**-0.149**	**-14.71**
Summer * 2002	**-0.095**	**-7.31**	0.003	0.24	**-0.091**	**-10.96**
Summer * 2003	**-0.059**	**-4.00**	0.005	0.43	**-0.060**	**-6.33**
SIC 4. Utilities/water supply	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.014	3.23	0.013	2.99	0.004	1.86
CDD squared	0.000	-1.12	0.000	-0.65	0.000	-1.95
HDD	0.005	1.14	0.002	0.44	0.005	1.95
HDD squared	-0.001	-2.39	0.000	-0.38	-0.001	-4.14
Summer * 2001	0.060	2.20	0.081	2.89	-0.020	-1.43
Summer * 2002	**-0.104**	**-4.55**	0.002	0.09	**-0.112**	**-9.31**
Summer * 2003	0.010	0.38	0.026	1.00	-0.015	-1.13
SIC 5. Retail	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.007	0.83	0.000	-0.04	0.006	1.13
CDD squared	-0.001	-0.99	0.000	-0.02	0.000	-1.44
HDD	-0.010	-1.29	-0.018	-3.05	0.007	1.53
HDD squared	0.000	0.06	0.001	1.39	0.000	-1.56
Summer * 2001	-0.027	-0.58	0.001	0.03	-0.008	-0.29
Summer * 2002	0.031	0.78	0.042	1.27	0.010	0.40
Summer * 2003	-0.045	-0.98	-0.013	-0.38	-0.018	-0.63
SIC 6. Office buildings	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.011	9.00	0.008	6.94	0.002	4.69
CDD squared	0.000	-2.39	0.000	-1.00	0.000	-2.69
HDD	-0.019	-18.14	-0.013	-12.82	-0.007	-19.69
HDD squared	0.001	8.10	0.000	6.21	0.000	8.07
Summer * 2001	**-0.015**	**-2.53**	0.006	1.02	**-0.007**	**-3.01**
Summer * 2002	**-0.012**	**-2.33**	0.000	0.07	0.003	1.79
Summer * 2003	0.003	0.61	0.010	2.11	0.002	1.36
SIC 7. Services	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
CDD	0.014	1.75	0.012	1.40	0.006	5.14
CDD squared	0.000	-0.50	0.000	-0.78	0.000	0.70
HDD	-0.030	-3.48	-0.023	-2.68	-0.005	-4.16
HDD squared	0.002	3.67	0.002	3.32	0.000	1.46
Summer * 2001	0.083	1.71	0.065	1.26	**-0.030**	**-4.60**
Summer * 2002	0.061	1.65	0.029	0.71	**-0.014**	**-2.73**
Summer * 2003	0.148	3.50	0.105	2.41	0.013	2.32

season. Perhaps more importantly, the signs could indicate that the set point for calculating CDD/HDD may have been set too high. Consequently, we could be picking up temperatures through the HDD variable at which customers already consume electricity to cool buildings. Since the variables are picking up statistically significant weather effects, we retain them as calculated.

Seasonal pricing effects. Having attempted to control for the effect of weather in several ways, we turn to our seasonal pricing variable to examine potential customer peak-period price response. The coefficients on the interactions between Summer and Year dummy variables are designed to represent the effect of the seasonal price difference, net of weather effects. We would expect to see a negative Summer period coefficient in the peak period *level* regressions if customers reduced consumption in that period in response to the higher peak-period prices. Such reductions may or may not also imply a negative coefficient in the peak *share* regressions, depending on how the customers may have modified usage in the remainder of the day. Alternatively, customers' usage in the peak period could be higher absolutely, reflected by a positive coefficient in the level regressions, but lower in a relative sense if the increase were less than the increase in total daily use. Either coefficient pattern could imply peak-period price response. Complicating matters, however, any seasonal differences in daytime demand, and any nonlinear weather effects beyond those captured in the quadratic CDD terms, will also potentially be captured in the summer interaction variables, and thus confound the search for a price response effect.

In fact, for the A10 customers few negative coefficients appear on the Summer interactive variables in the pooled regressions across the various SIC groups. For SIC 2, in the SFO region, there are statistically significant negative coefficients on the summer variables in the daily use model. Viewing results in the "Daily use" column, customers decreased their overall use in the Summers of both 2002 and 2003 by about 2.8 percent. As implied by the relative magnitudes of the coefficients in the first two regressions, the share of electricity used in the peak period fell by a statistically significant amount in the summer of 2002, but this reduction was reversed in 2003.

For Summer 2003 in SIC 4, the negative coefficients suggest that electricity consumption in period 3 dropped substantially in the SFO weather zone. Customers in SIC 4 consumed 14.7 percent less in the peak time period during the summer relative to the non-summer (April) period. This decline also resulted in a significant shift in the *share* of electricity consumed in that period. Overall, SIC 4 saw a significant increase in total use in 2003 over 2002 (in results not presented), but a significant decline in the high-price summer peak period, a significant decline in the share used in the high price period, and a (not-significant) decline in overall daily summer usage. This pattern of negative coefficients is consistent with consumer price response. However, in the previous Summer of 2002, these same customers used more electricity overall, and used a greater share in the high-price period. This reduction in peak-period use between 2002 and 2003 would be consistent with customers learning from the Interact data or making adjustments in response to the new TOU prices.

For A10 Tariff customers outside the SFO weather zone, the story is similar. Coefficients on the weather variables were typically statistically significant, especially for the groups containing retail (SIC 5) and office buildings (SIC 6). Summer variables did not indicate widespread price response. In the few cases where negative coefficients appear, they are largely isolated and do not consistently point toward price response. For instance, SIC 2 customers significantly reduced their summer daily use and share of use in the peak pricing period, but the level of electricity consumed in that period increased significantly. In contrast to SIC 4 customers in the SFO weather zone, SIC 4 customers elsewhere in aggregate did not appear to reduce use in the peak pricing period. In fact, the non-SFO region customers increased their levels of use in the peak period in both years.

Results for E19 customers, presented in Table 6.4, show somewhat greater evidence of TOU price response, particularly in the two manufacturing SICs (2 and 3) and in SIC 4. Specifically, the *share* of peak usage fell significantly in both summers for all three SICs in the non-SFO weather zones, as well as for SIC 7 in 2002. In addition, the *level* of peak usage fell in SICs 3 and 4 (2002). In the SFO weather zone, the share of usage fell in SICs 3 and 4.

Finally, results for PG&E's larger E20 customers show even greater aggregate response to TOU prices.[12] Results in Table 6.5 suggest that the manufacturing customers in SICs 2, 3 and 4 (in 2002) responded strongly to peak TOU summer prices. Customers in SIC 2 significantly reduced use during the summer peak price period by 4 percent in 2001, 4.9 percent in 2002 and 3.6 percent in 2003 (not quite significantly). These declines also produced significant reductions in the share of electricity used during the high price period. Similar usage shifts occurred in SIC 3, which reduced use during the summer peak price period by 15.6, 9.5 and 5.9 percent in 2001, 2002 and 2003 respectively. Customers in SIC 4 reduced summer peak period use by 10 percent in 2002, but that reduction did not appear to carry over into 2003. Finally, SIC 6 showed evidence of small but statistically significant reductions in summer peak-period use in 2001 and 2002, though not in 2003, and SIC 7 experienced reductions in summer peak usage *shares* in 2001 and 2002.

Experience and intuition suggest that manufacturing customers and larger customers are likely to be more price responsive than commercial and smaller customers. This may be due to flexibility afforded by manufacturing processes (relative to retail establishments or office buildings) and the increased share of electricity in total production costs for large firms, or because of some combination of these. The relationship between size and price responsiveness was exhibited in the pooled results by the evidence of greater price responsive behavior of E20 customers relative to the smaller E19 and A10 customers, and that of the E19 customers relative to A10. In addition, among E19 and E20 customers, manufacturing industries (SICs 2-4) were more price responsive than customers in other industries. Note also that the E19 and E20 customers faced a substantially stronger summer TOU price signal than did the A10 customers.

In all, the pooled regression analysis results for PG&E provide sparse evidence of average, or overall customer price response to the summer TOU peak prices faced by the medium-sized commercial and industrial customers in the A10 groups, and only modest evidence of TOU price response in the E19 groups. To the extent that such price response may actually exist, our approach of using seasonal dummy variables within daily periods appeared to be limited in its ability to distinguish price effects from possible unexplained seasonal effects at a pooled level. This is likely due in part to the existence of substantial unexplained usage variation that is correlated with the seasonal and daily patterns of TOU tariffs, such as seasonal sales or

[12] Only customer accounts with maximum demand less than 5,000 kW were included in the analysis. The size restriction was designed to exclude unusually large and unique customers that would likely be least affected by the installation of the RTEM equipment.

production changes and seasonal weather effects that are not fully captured by the daily weather variables used in the regression equations. These unexplained effects could swamp any contemporaneous TOU price effects.

Individual Customer Price Response Estimation

To explore the extent to which price response may take place at the individual customer level and vary across customers, we applied our basic regression model to data for individual customers. We continued to focus on the three electricity use variables presented in the previous section: total daily use, the level of use in the peak period, and the share of use in the peak period. The customer level regressions provide a large number of individual customer price response estimates. Due to the number of customers analyzed, the individual results are summarized in a series of tables and figures rather than being presented individually.

A10 customers. We first present summary information on the sign and significance level of the individual-customer estimated coefficients on the key Summer variable for each of the three usage measures. Table 6.6 shows sign and significance percentages for the coefficient estimates for A10 customers, by SIC group. Given the pooled results, it is perhaps unsurprising that these results indicate that across all SICs less than half of customers have negative values in either summer period for the coefficients that we interpret as indicative of TOU price response—the level and share of use in the peak period. For 2002 and 2003, about 40 percent of the summer peak period level coefficients were negative, and 11 to 16 percent were negative and statistically significant. The percentage of negative and significant coefficients for summer peak period usage changes ranged across SIC groups from 7 to 22 percent, with the highest values typically in SIC 2 and 3.

Also included in the table are columns showing coefficients for 2001, prior to the installation of RTEM equipment. These results are for a subset of the A10 customers for whom hourly load data were available for 2001, presumably those accounts that made up PG&E's class load research sample or were sufficiently large that interval meters had been installed. The results indicate that the proportion of significantly price responsive customers was substantially greater in 2001 than in the subsequent two years for each of the SIC groups. We re-calculated the percentages for 2002 and 2003 for only the subset for which data were available in 2001, and found that they were nearly identical to those for the entire class shown in Table 6.6. We conclude that the proportion of significantly price responsive customers was substantially greater in 2001 than in the subsequent two years for each of the SIC groups, which likely reflects the non-price effects of the public encouragement to reduce load during peak summer periods in 2001 as a way of preventing the capacity shortages that occurred the previous summer.

E19 customers. Similar results are presented in Table 6.7 for E19 customers. Again, consistent with the pooled results, less than half of customers have negative peak-price period coefficient estimates consistent with TOU price response. However, a small but significant proportion, ranging from 5 to 20 percent, exhibited significant reductions in either peak period usage or peak usage share, while another 20 to 30 percent exhibited reductions that were not statistically significant. The largest proportions of price-responsive customers were found in SIC 3 and 4. Also included in the table are columns showing coefficients for 2001, prior to the installation of RTEM equipment. These results similarly indicate that the proportion of significantly price

Table 6.6. Individual Customer Coefficient Summary – A10 Customer Groups

	Peak Pricing Period Level			Daily Use			Peak Pricing Period Share		
All Customers	2001	2002	2003	2001	2002	2003	2001	2002	2003
Significantly > 0	26%	29%	28%	29%	34%	32%	20%	20%	19%
Coef > 0	52%	60%	64%	49%	62%	59%	49%	53%	57%
Coef < 0	48%	40%	36%	51%	38%	41%	51%	47%	43%
Significantly < 0	**26%**	**16%**	**11%**	**32%**	**16%**	**16%**	**18%**	**13%**	**9%**
Number of Estimated Coefficients	395	1,068	1,169	383	1,068	1,167	395	1,067	1,169
SIC 2. Food/paper/chemicals									
Significantly > 0	26%	31%	25%	42%	21%	19%	16%	13%	10%
Coef > 0	64%	59%	56%	63%	54%	44%	51%	46%	52%
Coef < 0	36%	41%	44%	37%	46%	56%	49%	54%	48%
Significantly < 0	**16%**	**15%**	**17%**	**22%**	**19%**	**26%**	**15%**	**14%**	**10%**
Number	61	165	166	59	165	166	61	165	166
SIC 3. Plastic/stone/metals									
Significantly > 0	22%	23%	23%	25%	29%	27%	28%	15%	18%
Coef > 0	47%	54%	59%	53%	57%	55%	48%	49%	57%
Coef < 0	53%	46%	41%	47%	43%	45%	52%	51%	43%
Significantly < 0	**27%**	**19%**	**12%**	**32%**	**19%**	**18%**	**16%**	**14%**	**9%**
Number	88	266	267	92	266	267	88	266	267
SIC 4. Utilities/water supply									
Significantly > 0	20%	30%	25%	32%	29%	21%	2%	16%	13%
Coef > 0	56%	61%	65%	68%	60%	57%	37%	55%	49%
Coef < 0	44%	39%	35%	32%	40%	43%	63%	45%	51%
Significantly < 0	**24%**	**11%**	**11%**	**19%**	**16%**	**13%**	**24%**	**13%**	**6%**
Number	41	96	101	37	96	99	41	95	101
SIC 5. Retail									
Significantly > 0	26%	40%	42%	24%	43%	37%	11%	23%	21%
Coef > 0	53%	73%	72%	47%	74%	63%	53%	54%	64%
Coef < 0	47%	27%	28%	53%	26%	37%	47%	46%	36%
Significantly < 0	**21%**	**7%**	**8%**	**27%**	**12%**	**14%**	**15%**	**13%**	**7%**
Number	47	142	144	45	142	144	47	142	144
SIC 6. Office buildings									
Significantly > 0	30%	27%	27%	25%	40%	40%	21%	27%	25%
Coef > 0	48%	58%	66%	32%	65%	67%	49%	58%	58%
Coef < 0	52%	42%	34%	68%	35%	33%	51%	42%	42%
Significantly < 0	**32%**	**22%**	**10%**	**47%**	**15%**	**13%**	**22%**	**11%**	**11%**
Number	106	274	366	99	274	366	106	274	366
SIC 7. Services									
Significantly > 0	27%	33%	30%	29%	42%	37%	29%	22%	24%
Coef > 0	54%	66%	70%	49%	66%	62%	56%	57%	62%
Coef < 0	46%	34%	30%	51%	34%	38%	44%	43%	38%
Significantly < 0	**27%**	**14%**	**11%**	**31%**	**15%**	**17%**	**19%**	**14%**	**9%**
Number	52	125	125	51	125	125	52	125	125

Table 6.7 Individual Customer Coefficient Summary – E19 Customer Groups

	Peak Pricing Period Level			Daily Use			Peak Pricing Period Share		
All Customers	2001	2002	2003	2001	2002	2003	2001	2002	2003
Significantly > 0	22%	32%	26%	26%	33%	32%	13%	15%	14%
Coef > 0	44%	60%	58%	47%	59%	55%	38%	49%	54%
Coef < 0	56%	40%	42%	53%	41%	45%	62%	51%	46%
Significantly < 0	**32%**	**16%**	**18%**	**29%**	**18%**	**18%**	**26%**	**14%**	**13%**
Number of Estimated Coefficients	389	511	553	320	511	553	389	511	553
SIC 2. Food/paper/chemicals									
Significantly > 0	21%	35%	27%	20%	22%	26%	10%	15%	12%
Coef > 0	52%	63%	68%	45%	52%	55%	32%	48%	53%
Coef < 0	48%	37%	32%	55%	48%	45%	68%	52%	47%
Significantly < 0	**21%**	**14%**	**13%**	**20%**	**21%**	**19%**	**30%**	**13%**	**12%**
Number	111	155	163	98	155	163	111	155	163
SIC 3. Plastic/stone/metals									
Significantly > 0	19%	30%	28%	24%	42%	35%	17%	17%	15%
Coef > 0	39%	58%	54%	41%	66%	57%	43%	51%	58%
Coef < 0	61%	42%	46%	59%	34%	43%	57%	49%	42%
Significantly < 0	**37%**	**17%**	**19%**	**36%**	**14%**	**14%**	**23%**	**14%**	**8%**
Number	155	187	207	124	187	207	155	187	207
SIC 4. Utilities/water supply									
Significantly > 0	28%	30%	24%	34%	34%	33%	11%	12%	16%
Coef > 0	45%	60%	54%	55%	57%	53%	37%	49%	52%
Coef < 0	55%	40%	46%	45%	43%	47%	63%	51%	48%
Significantly < 0	**35%**	**18%**	**20%**	**29%**	**19%**	**21%**	**27%**	**14%**	**19%**
Number	123	169	183	98	169	183	123	169	183
SIC 5. Retail									
Significantly > 0	30%	41%	39%	28%	40%	42%	21%	21%	24%
Coef > 0	49%	65%	71%	46%	67%	69%	45%	56%	61%
Coef < 0	51%	35%	29%	54%	33%	31%	55%	44%	39%
Significantly < 0	**32%**	**17%**	**11%**	**42%**	**8%**	**13%**	**26%**	**13%**	**8%**
Number	163	234	241	120	234	241	163	234	241
SIC 6. Office buildings									
Significantly > 0	16%	30%	31%	30%	47%	29%	13%	22%	21%
Coef > 0	34%	63%	62%	57%	68%	58%	37%	57%	59%
Coef < 0	66%	37%	38%	43%	32%	42%	63%	43%	41%
Significantly < 0	**35%**	**16%**	**13%**	**23%**	**18%**	**17%**	**38%**	**15%**	**10%**
Number	82	103	173	69	103	173	82	103	173
SIC 7. Services									
Significantly > 0	32%	41%	37%	33%	29%	37%	19%	20%	20%
Coef > 0	52%	65%	77%	57%	60%	69%	54%	53%	65%
Coef < 0	48%	35%	23%	43%	40%	31%	46%	47%	35%
Significantly < 0	**24%**	**12%**	**5%**	**21%**	**20%**	**12%**	**24%**	**11%**	**7%**
Number	108	161	169	89	161	169	108	161	169

responsive customers was substantially greater in 2001 than in the subsequent two years for each of the SIC groups.

E20 customers. Finally, results for E20 customers are summarized in Table 6.8. As suggested by the pooled estimation results, approximately half of the customer accounts had negative level coefficients, with approximately 20 percent being statistically significant. The most price-responsive SIC groups were 2 through 5, while the least responsive were SIC 6 and 7. The pattern of coefficients over the three years of 2001 through 2003 was similar to those in the previous two tables, although the differences between 2001 and the following two years were not as great for the generally more price-responsive E20 customers than for the smaller A10 and E19 customers.

The following observations may be made about the distributions in Figures 6.6 through 6.8:

- In nearly every SIC group in each rate class, approximately thirty to forty percent of the level equation coefficients are negative, suggesting some degree of TOU price response;
- In nearly every SIC group, approximately 10 percent of the customer accounts show evidence of strong price responsiveness, suggesting summer peak load reductions of 20 percent or more, with the larger customer accounts in SIC 2 through 4 in rate classes E19 and E20 showing the largest load reductions.
- The coefficients in the share equations (indicated by the dashed lines) suggest three general patterns. First, in many cases the customers with the largest (negative) *level* coefficient also have negative *share* coefficients, indicating very strong evidence of peak period TOU price response that is distinct from overall daily usage reductions. Second, a few of the cases of large negative level coefficients are paired with a positive share coefficient. This seems to occur in cases where the total daily usage, including peak period usage, falls during the summer months, producing a zero or positive share coefficient. In these cases, it is difficult to know whether the load change represents a price response or some other seasonal usage change.

  Third, a few of the customers with the largest *positive* level coefficients have large *negative* coefficients in the share equation. This pattern is consistent with an increase in summer peak period usage that is proportionately less than an increase in total summer daily usage, which could also be interpreted as a form of TOU price response. Fourth, in the wide middle range of slightly negative to slightly positive level coefficients, the share coefficients generally show small positive values, possibly representing a higher share of peak usage due to weather effects that are not captured completely by the weather variables in the regression.

Table 6.8 Individual Customer Coefficient Summary – E20 Customer Groups

	Peak Pricing Period Level			Daily Use			Peak Pricing Period Share		
All Manufacturing Customers	2001	2002	2003	2001	2002	2003	2001	2002	2003
t-stat > 1.95	15%	23%	23%	19%	25%	22%	6%	7%	11%
t-stat > 0	43%	50%	54%	48%	54%	52%	27%	38%	48%
t-stat < 0	57%	50%	46%	52%	46%	48%	73%	62%	52%
t-stat < -1.95	**29%**	**22%**	**17%**	**25%**	**20%**	**21%**	**29%**	**20%**	**13%**
Number of Estimated Coefficients	259	265	281	257	265	282	259	265	281
SIC 2									
t-stat > 1.95	18%	29%	21%	14%	24%	15%	5%	2%	9%
t-stat > 0	48%	60%	56%	46%	58%	47%	26%	35%	49%
t-stat < 0	52%	40%	44%	54%	42%	53%	74%	65%	51%
t-stat < -1.95	**28%**	**14%**	**17%**	**22%**	**20%**	**22%**	**30%**	**22%**	**18%**
Number	98	99	98	97	99	99	98	99	98
SIC 3									
t-stat > 1.95	5%	13%	24%	21%	21%	27%	3%	6%	8%
t-stat > 0	37%	41%	49%	48%	43%	60%	18%	40%	40%
t-stat < 0	63%	59%	51%	52%	57%	40%	82%	60%	60%
t-stat < -1.95	**38%**	**30%**	**21%**	**21%**	**16%**	**11%**	**35%**	**16%**	**13%**
Number	60	63	63	58	63	63	60	63	63
SIC 4									
t-stat > 1.95	28%	27%	21%	24%	24%	23%	8%	8%	15%
t-stat > 0	58%	51%	56%	51%	59%	41%	28%	32%	44%
t-stat < 0	42%	49%	44%	49%	41%	59%	72%	68%	56%
t-stat < -1.95	**25%**	**30%**	**21%**	**24%**	**22%**	**23%**	**17%**	**19%**	**13%**
Number	36	37	39	37	37	39	36	37	39
SIC 5									
t-stat > 1.95	17%	0%	42%	33%	8%	25%	8%	25%	17%
t-stat > 0	33%	33%	50%	67%	58%	50%	33%	50%	58%
t-stat < 0	67%	67%	50%	33%	42%	50%	67%	50%	42%
t-stat < -1.95	**33%**	**17%**	**25%**	**17%**	**8%**	**25%**	**33%**	**25%**	**17%**
Number	12	12	12	12	12	12	12	12	12
SIC 6									
t-stat > 1.95	7%	20%	22%	21%	23%	24%	7%	17%	16%
t-stat > 0	27%	37%	51%	48%	47%	60%	33%	57%	53%
t-stat < 0	73%	63%	49%	52%	53%	40%	67%	43%	47%
t-stat < -1.95	**23%**	**27%**	**11%**	**31%**	**33%**	**27%**	**30%**	**10%**	**7%**
Number	30	30	45	29	30	45	30	30	45
SIC 7									
t-stat > 1.95	13%	33%	21%	21%	54%	29%	13%	4%	13%
t-stat > 0	39%	58%	63%	42%	63%	50%	39%	29%	63%
t-stat < 0	61%	42%	38%	58%	38%	50%	61%	71%	38%
t-stat < -1.95	**26%**	**13%**	**8%**	**46%**	**17%**	**25%**	**30%**	**29%**	**0%**
Number	23	24	24	24	24	24	23	24	24

Figure 6.6 Distribution of Individual Customer Coefficients – A10

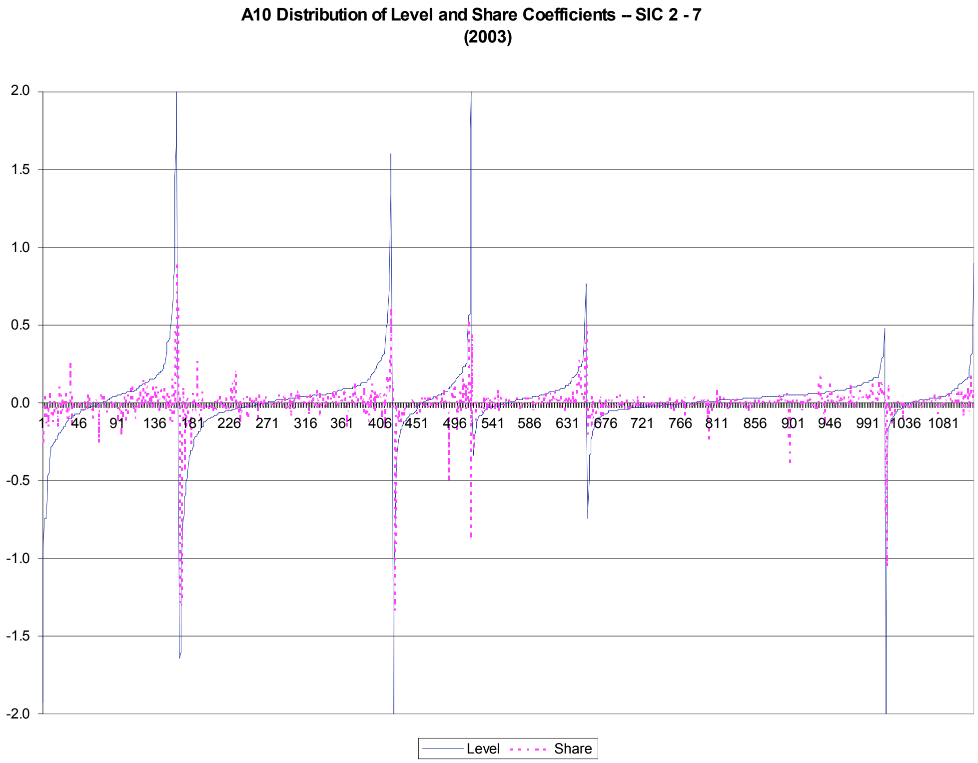


Figure 6.7 Distribution of Individual Customer Coefficients – E19

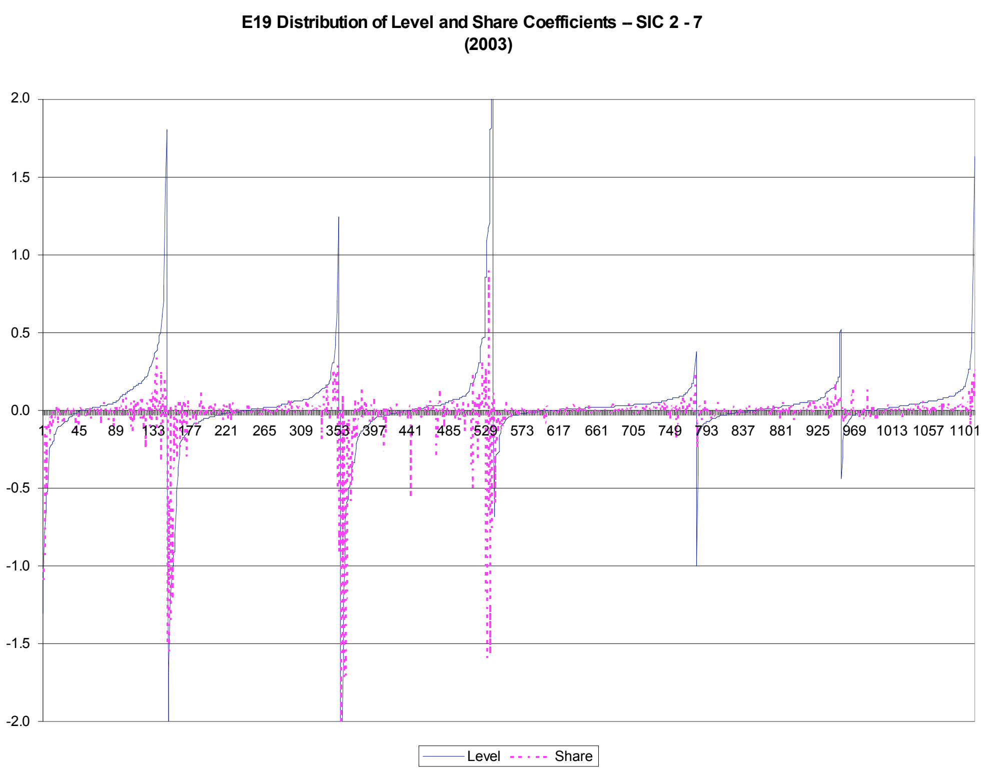
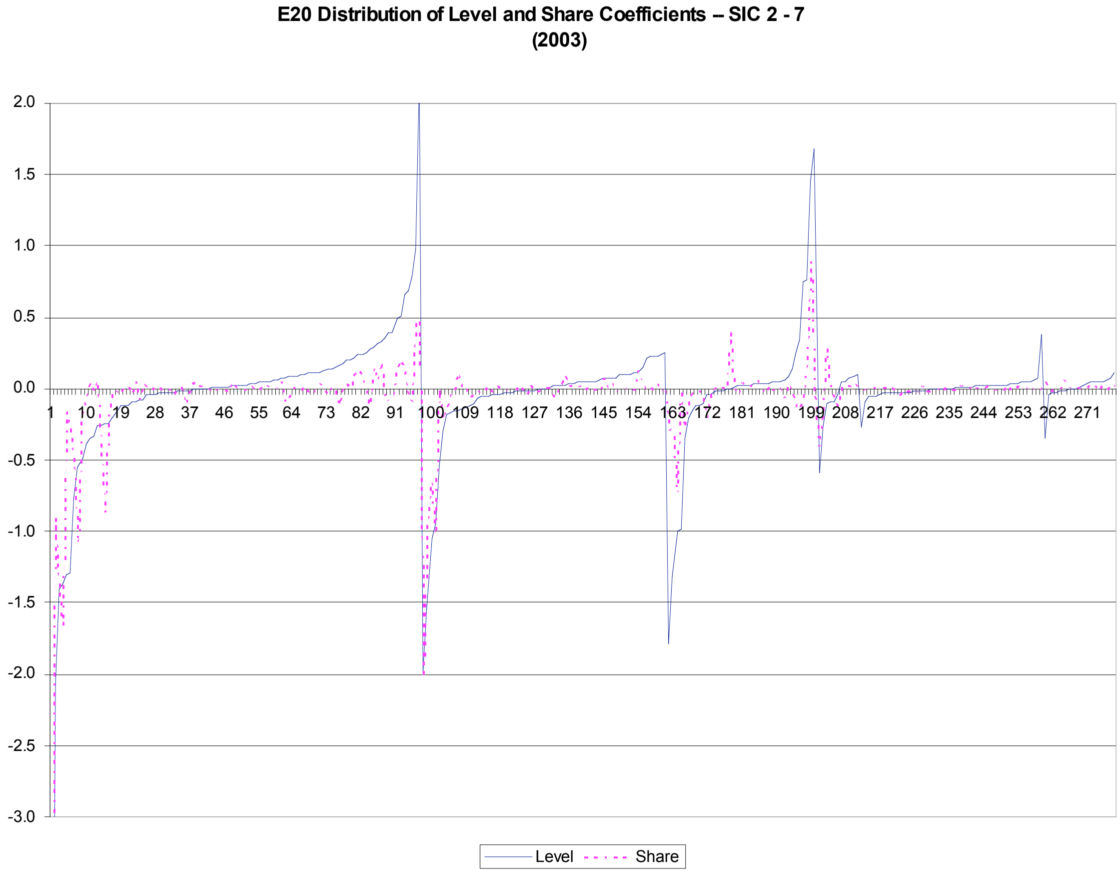


Figure 6.8 Distribution of Individual Customer Coefficients – E20



- It is difficult to know what to make of the perhaps 20 to 40 percent of customers with positive coefficients in both the level and share equations. However, it is highly illogical to attribute such findings as evidence of customers *increasing* peak period consumption in response to higher prices. More likely, some customers' summer usage patterns are affected by factors that are not well explained by the limited data available to this analysis. One possibility is that some customers' weather sensitivity consists of both an overall seasonal effect that is present for the entire summer (and is thus coincident with the period of high peak prices) and an effect that varies due to daily weather variations. To the extent that our CDD variables capture only the second type of effect, then the first type may be picked up by the summer coefficient.

InterAct Software Effects

Finally, we expanded the pooled analysis to incorporate information on A10 consumers' use of PG&E's InterAct software in an attempt to estimate the possible effect of customer use of the website on their price responsive behavior. PG&E provided data on InterAct events, which was organized with a "channel" identifier. Each channel was assigned several dates, including an "as of" date, which we understand represents the date customers could begin to use the program after signing up to gain access, and a "log in" date that represents the *last* time the channel was used to access usage information (*i.e.*, the last time before the date on which the data were extracted for delivery to us). PG&E provided a map that allowed us to match channel information to customer account numbers, and thus to their electricity use. Customers were observed with up to twelve entries for a single channel. We were not provided information on the relationship between multiple channel entries and other customer-level information, such as electricity use and billing information, so we assumed that all channel entries represented unique paths to the same account information by multiple possible users at a given customer site. In the data provided, over 1,600 customers were observed using the InterAct software through one or more paths.

To consolidate the path information, we matched each path to the relevant customer. We then differenced the "log in" and "as of" dates, and kept the information on the longest span, which we interpreted as continued use of the system after initial login. We did not observe the number of times that customers accessed their electricity usage during that span. That is, we did not know whether customers used the particular path frequently or infrequently. To analyze InterAct, we defined two time-interval variables based on the "as of" and "log in" dates. Specifically, we constructed two dummy variables, the first indicating the period between the "as of" date and the "log in" date, and the second indicating the period after the last log in through the remainder of observations (thus representing an indication of relatively recent use). For these two variables to be activated in our analysis, we also required that customers have at least thirty days between their "as of" and "log in" dates, assuming that customers who are logging in after longer periods of time are more likely to be active users of the Interact software. A large proportion of customers were observed to log in the last time on the "as of" date. The minimum period threshold resulted in around 40 percent of customers with observed log-ins being omitted from the analysis.

Table 6.9 presents selected results from our analysis. We have restricted the regression models to the customers who used Interact software and who passed our minimum period threshold. We present summer pricing period variables and our Interact variables for Daily Use, Peak Period Use, and Peak Period Shares for each of the industries being analyzed. In the first panel of results, we establish baseline coefficients for summer pricing period variables for these customers. These are interesting for two reasons—one is that these customers may be more price-responsive as a group to begin with. That is, the same unobserved characteristics that made these customers access their accounts may have already made them price sensitive. Another important reason to monitor these coefficients is because the model shown in the second panel of results interacts a summer pricing period variable with the “as of” Interact software variable. It is of interest to monitor the statistical properties in these estimates when interacting the variables.

A couple of notes should be made regarding these regressions relative to the above results. In these regressions, no monthly restrictions have been made. Here we are primarily trying to identify the effects of InterAct software use, which are presumably less associated with weather and other seasonal demand factors than the explicitly seasonal pricing periods that we evaluated above. The additional observations will likely be useful in identifying the effects we are interested in. The other difference is that we combined weather zones. This was due to the small number of InterAct software participants in some in7dustry-weather zones. The process of matching customers across data sources, segmenting the observations by industry and tariffs, and screening data resulted in a sharp decline in the number of customers available for analysis. It is beneficial to combine customers across some characteristics, especially if those characteristics are unlikely to be associated with Interact use.

Table 6.9 InterAct Software Effects– A10 Customer Groups

	Sample Restricted Only to Customers Using Interact											
	Peak Level		Daily Use		Peak Share		Peak Level		Daily Use		Peak Share	
SIC 2. Food/paper/chemicals	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.131	5.74	0.084	4.10	0.036	4.51	0.094	3.85	0.022	1.00	0.036	4.23
Summer * 2003	0.204	8.10	0.144	5.96	0.031	3.53	0.097	2.35	-0.014	-0.37	0.036	2.50
Period after "as of" date	--		--		--		**-0.130**	**-5.66**	**-0.191**	**-8.24**	**-0.012**	**-1.50**
Summer * Period after "as of" date	--		--		--		0.143	4.07	0.166	5.40	-0.001	-0.11
Observations		9,081										
Customers		21										
SIC 3. Plastic/stone/metals	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.084	6.52	0.041	3.67	0.047	9.58	0.083	6.35	0.042	3.66	0.047	9.37
Summer * 2003	0.035	2.45	-0.024	-1.80	0.071	12.79	0.041	1.98	-0.022	-1.21	0.077	9.71
Period after "as of" date	--		--		--		-0.019	-1.36	0.009	0.66	**-0.015**	**-2.74**
Summer * Period after "as of" date	--		--		--		0.000	0.02	-0.003	-0.16	-0.002	-0.24
Observations		19,361										
Customers		44										
SIC 4. Utilities/water supply	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.003	0.10	0.006	0.23	-0.017	-0.88	0.073	2.17	0.026	0.93	0.028	1.30
Summer * 2003	-0.354	-10.79	-0.306	-10.15	-0.089	-4.30	-0.205	-4.89	-0.246	-6.59	-0.009	-0.33
Period after "as of" date	--		--		--		0.038	1.06	**-0.098**	**-3.24**	0.117	5.23
Summer * Period after "as of" date	--		--		--		**-0.198**	**-5.49**	**-0.076**	**-2.49**	**-0.121**	**-5.30**
Observations		7,820										
Customers		20										
SIC 5. Retail	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.113	11.43	0.051	5.83	0.051	11.68	0.118	11.32	0.039	4.01	0.060	13.14
Summer * 2003	0.124	11.17	0.063	5.94	0.030	6.22	0.130	7.25	0.016	0.88	0.066	8.38
Period after "as of" date	--		--		--		0.053	4.80	-0.020	-1.59	0.027	5.46
Summer * Period after "as of" date	--		--		--		-0.014	-0.92	0.050	3.47	**-0.041**	**-5.99**
Observations		6,591										
Customers		15										
SIC 6. Office buildings	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.070	10.59	0.063	10.58	0.016	7.05	0.086	12.14	0.075	11.73	0.024	9.63
Summer * 2003	0.048	7.14	0.042	6.44	0.029	12.02	0.087	8.57	0.073	7.67	0.042	11.87
Period after "as of" date	--		--		--		0.045	6.44	0.031	4.74	0.033	13.56
Summer * Period after "as of" date	--		--		--		**-0.051**	**-5.76**	**-0.036**	**-4.49**	**-0.022**	**-6.93**
Observations		15,581										
Customers		43										
SIC 7. Services	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Summer * 2002	0.138	4.75	0.081	3.17	0.036	3.00	0.145	4.87	0.077	2.92	0.034	2.75
Summer * 2003	0.097	2.96	0.017	0.55	0.020	1.49	0.184	3.67	0.074	1.62	0.028	1.33
Period after "as of" date	--		--		--		-0.045	-1.37	**-0.073**	**-2.39**	**-0.035**	**-2.53**
Summer * Period after "as of" date	--		--		--		-0.084	-1.78	-0.060	-1.47	0.002	0.11
Observations		7,453										
Customers		17										

In *Daily Use* regressions, several negative and significant coefficients (shown in bold) appear on the Interact software variables. In SIC 2, for instance, customers reduced daily use after log in by more than 19 percent, although the reduction did not hold during the summer months. Significantly negative effects also occurred in daily use in SIC 4 and 7. Significant *summer* daily usage reductions were observed in SIC 4 and 6.

Negative coefficients in the *peak pricing period* regressions were found in most of the same SIC groups. In two of the groups, SIC 4 and 6, negative and statistically significant coefficients were found in both the peak usage level and share equations. These suggest that the average price response of customers in these two groups increased in the period after they began using the InterAct website software. For example, in SIC 4, summer peak period usage fell by 35 percent in 2003, with about half of that reduction apparently attributable to the period after the accounts began using the InterAct website.

Aggregate Estimates of TOU Price Response

This section uses the results of the individual customer analyses reported above to produce estimates of the overall, or aggregate level of TOU price response that was present in each of the SIC groups in the summer months of 2002 and 2003. The estimates were derived in the following series of steps:

- Calculate the average weekday load during the mid-summer period of July 16–September 15 for each of the SIC groups in the A10, E19 and E20 rate classes;
- Accumulate the summer peak period load reductions that are implied by the negative coefficients on the summer peak period level equations across all customer accounts in each rate class and SIC group. We used a relatively restrictive screen in making these load reduction calculations, essentially requiring the peak period level coefficient to be negative and significant, the corresponding share coefficient to also be negative, and the peak coefficient to be larger in absolute value than the average daily coefficient, thus not attributing an overall reduction in summer usage to a TOU price response (we used those coefficients that were negative and statistically significant at a 10 percent level for a one-tailed test, which implied a t-statistic of approximately -1.3);
- Scale the actual summer peak loads and estimated TOU peak load reductions to the population level for the six SIC groups using the ratio of summer energy usage for all non-direct access customer accounts in those SICs for which billing data were supplied, to the summer energy usage for those accounts used in the individual customer regressions. These scaling factors averaged approximately 1.2 for the A10 class and 1.6 for the E19 class. Results for E20, which represent those accounts with maximum demands less than 5,000 kW, were not scaled.
- Report the aggregate amount of TOU price response and the percentage of the total load that we estimate would have occurred without the price response (*i.e.*, the sum of the *actual* aggregate summer weekday peak load and the amount of peak-period TOU load reductions).

The resulting loads and TOU peak load reductions are shown in Table 6.10. The total observed summer peak period loads total approximately 300 MW for A10, 600 MW for E19, and 557 MW for E20. Estimated TOU peak period load reductions amounted to 3.4, 10 and 19.6 MW respectively for the three rate classes, totaling approximately 33 MW. These load reductions represent from 1 to 3.4 percent of the total class loads.

Table 6.10. Aggregate TOU Summer Peak Load Reductions

PG&E	Ave. Peak Demand (MW)	Estimated TOU peak reduction	% Reduction
A10			
Industrial	122	2.5	2.1%
Commercial	178	0.8	0.5%
Total	300	3.4	1.1%
E19			
Industrial	291	8.6	3.0%
Commercial	318	1.3	0.4%
Total	609	10.0	1.6%
E20 (< 5 MW)			
Industrial	399	18.1	4.5%
Commercial	178	1.5	0.9%
Total	576	19.6	3.4%

Case Studies—Individual Customer Examples

A number of graphs are provided in the appendix to this section that illustrate examples of load profiles for a variety of individual customer accounts by SIC group in both the A10 and E19 rate classes. Each figure contains four weekday TOU-period load profiles, each representing an average across weekdays in April (when non-summer energy and demand charges apply) and May (when the Peak TOU energy and demand charges apply), for both 2002 and 2003. As with the aggregate loads shown earlier, the two April loads are shown as dashed lines, and the two loads for 2003 are shown in a broad line without individual data indicators. Also shown in the subtitle line are values of the six regression coefficients discussed in the results section above—the summer shift term for the Peak usage *level* equation, the Daily usage equation, and the Peak usage *share* equation, for both 2002 and 2003.

The load profiles were selected to illustrate the relationship between various combinations of estimated coefficients and the actual energy use patterns of the customers in the various groups. Some indicate obvious reductions in summer peak period usage or usage share that confirm the interpretation of the coefficients as representing peak-period price response. Others show lack of price response that is consistent with small and/or insignificant coefficients. Still others confirm the interpretation of a combination of a positive usage *share* coefficient and a negative peak *level* coefficient as representing price responsive behavior.

The selected customer accounts include some of the most clear and dramatic examples of customers reducing load during the peak period, and sometimes shifting it to other hours of the day. However, these examples should not be considered typical of the majority of accounts.

Conclusions

The non-experimental conditions of the RTEM project and the resulting data limited the nature of the analysis that could be conducted to assess the effect of the installation of the metering and communication software, and customers' potential access to their usage data via website software on their electricity usage patterns. In particular, the equipment was installed on all customer accounts of size greater than 200 kW, leaving no "control" customers that did not receive the equipment. Second, load data for the customers for whom new metering equipment was installed and which were switched to a new TOU rate were only available for the period after they began to face the new prices. Finally, the larger customer accounts in the E19 rate class, for whom load data were available for the period before gaining access to their usage data, saw no change in their existing TOU tariff.

As a result of these conditions, we developed an analysis approach for estimating customer response to TOU prices that involved the estimation of load changes due to the presence of the summer/non-summer differential between the effective energy price in the time period defined by the summer peak price. We also expanded the approach to examine the effect of customers' usage of PG&E's InterAct website software on their price response behavior.

We conducted two levels of analysis, one using pooled regression analysis to estimate price responsiveness at the aggregate rate class and SIC group level, and another applying regression analysis to data for individual customer accounts to estimate the range of TOU price response across customers. The pooled analysis found relatively little evidence of peak-period TOU price response on average for the A10 class, moderate price response for the E19 class, and substantial price response for the larger customers (> 1,000 kW), in the E20 rate class. For the most part, only for some SIC groups, particularly the manufacturing SICs of 2 and 3, and SIC 4, and primarily for the larger customer classes, were significant price response coefficients estimated.

However, an analysis of individual customer data suggests that averaging across customers in the pooled analysis masks the actual extent of TOU price response among individual customers. The individual customer analysis demonstrated that at least some fraction of customers in nearly all SIC groups (ranging from 10 to 20 percent) evidenced significant peak-period TOU price response in 2002 and 2003, while an additional comparable fraction appeared to respond in limited and not statistically significant ways. In addition, results for 2001 indicated substantially greater degrees of TOU price response in the summer peak period in nearly every rate class/SIC group, compared to their responsiveness in the subsequent years.

Using the price response estimates from the individual customer analysis, we calculated the total amount of implied TOU peak load reductions for each rate class and SIC group. The aggregate results suggest peak load reductions of 2.2, 7.5 and 17.4 MW for the A10, E19 and E20 rate classes respectively, for a total load reduction of 27.1 MW. This estimate does not include data for customers in agricultural operations, SIC 8 (including hospitals and schools) and 9 (Government), or E20 customers larger than 5,000 kW.

Finally, our analysis of the effect of customer use of the InterAct software found limited evidence of changes in consumer price response, suggesting that customers in at least two of the A10 SIC groups increased their peak period price response after establishing an InterAct account.

IMPLICATIONS FOR DEMAND RESPONSE PROGRAMS

As noted in Section 1, the original rationale for the installation of the AB29X (RTEM) equipment for customer accounts larger than 200 kW was to provide the infrastructure needed for the establishment of dynamic-pricing programs such as RTP. As the effort to design and implement RTP tariffs acceptable to all parties stalled, focus shifted to testing a variety of demand response programs aimed at reducing customer usage during periods of particularly high market costs. A recent report described the findings of a project designed to evaluate the performance and potential for several of these DR programs for each of the major California utilities, including critical peak pricing (CPP) and demand bidding programs (DBP).[13] The project was undertaken under the auspices of the collaborative Working Group 2, which was formed to study a variety of potential dynamic pricing and DR programs for California and assist in their design and implementation.

This section discusses possible implications of the findings in our analysis of existing customer TOU price response for the ongoing effort to establish effective demand response programs in California. The primary implications have to do with the extent of existing customer response to the utilities' current TOU tariffs, and what that means about customers' existing baseline loads and potential for providing load response through DR programs.

Conclusions From Recent DR Program Evaluation

The recent WG2 evaluation study involved an assessment of the programs' operations in 2004, a survey of non-participating consumers, and an evaluation of program impacts. Key conclusions included the following:

- The study found "significant challenges" in meeting target levels of participation and load reductions;
- The study reported an overall load reduction for CPP of approximately 8 MW across all utilities, approximately 60 percent of which was accounted for by PG&E;
- The study estimated potential CPP benefits to consumers in the range of 1 to 2 percent of annual bills, and reported that survey results indicated that relatively few customers would be willing to reduce load in exchange for such bill savings;
- Estimates of the market potential for DR load curtailments based on the customer survey ranged from a high of 1,600 MW (out of a total maximum demand of 10,000 MW) at artificially high DR payments designed to represent *sufficient financial motivation*; to 100 MW at more realistic potential benefits of less than 5 percent of annual bills.

The study's conclusions appear to contain an implicit assumption that customers' current loads have been essentially unaffected by the utilities' existing TOU demand and energy charges, and then pose the question of how many customers will be willing to participate in DR programs and modify their current usage pattern in return for the opportunity to achieve relatively modest bill

[13] "Working Group 2 Demand Response Program Evaluation – Program Year 2004," prepared for WG2 Measurement and Evaluation Committee, by Quantum Consulting Inc. and Summit Blue Consulting, LLC, December 2004.

savings. However, the results presented in Sections 5 and 6 of the present evaluation of SCE and PG&E customers' existing TOU load response have shown that a modest but significant portion of customers—presumably those most willing and able to do so—already reduce their load during the summer peak periods, presumably doing so nearly every weekday of the summer billing period. Section 6.4 provided estimates of aggregate TOU peak-period price response for PG&E amounting to 27.1 MW. The following section discusses potential implications of these results for DR programs in California.

Implications of Existing TOU Price Response

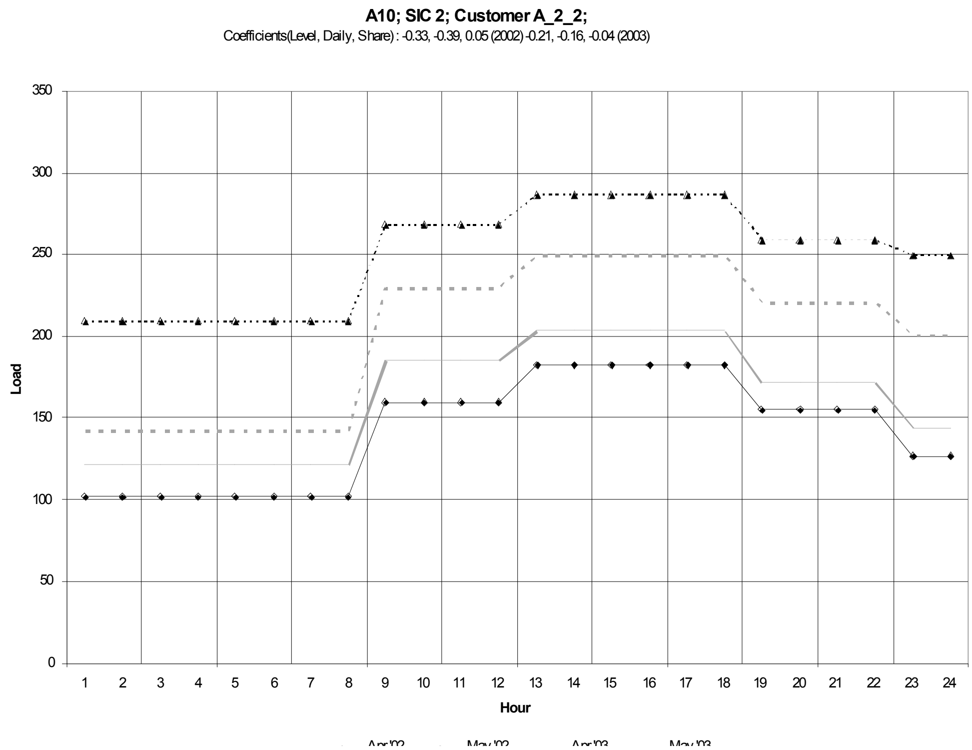
The results presented in Sections 5 and 6 reveal that a number of SCE and PG&E commercial and industrial customers already respond to the substantial peak period price differential of more than 2 to 1 between summer (June through September for SCE, and May through October for PG&E) and non-summer months. These are presumably the customers whose loads are most flexible, and for whom electricity costs are most sensitive, as their peak-period load reductions and load shifting have to take place every weekday for four to six months of the year to achieve full savings. Our analysis for PG&E indicates that some customers in SIC 2 through 4 are able to reduce summer peak load levels by amounts ranging from 5 percent to nearly 100 percent. These estimates are confirmed by average daily load profiles illustrated for a number of representative price-responsive customers.

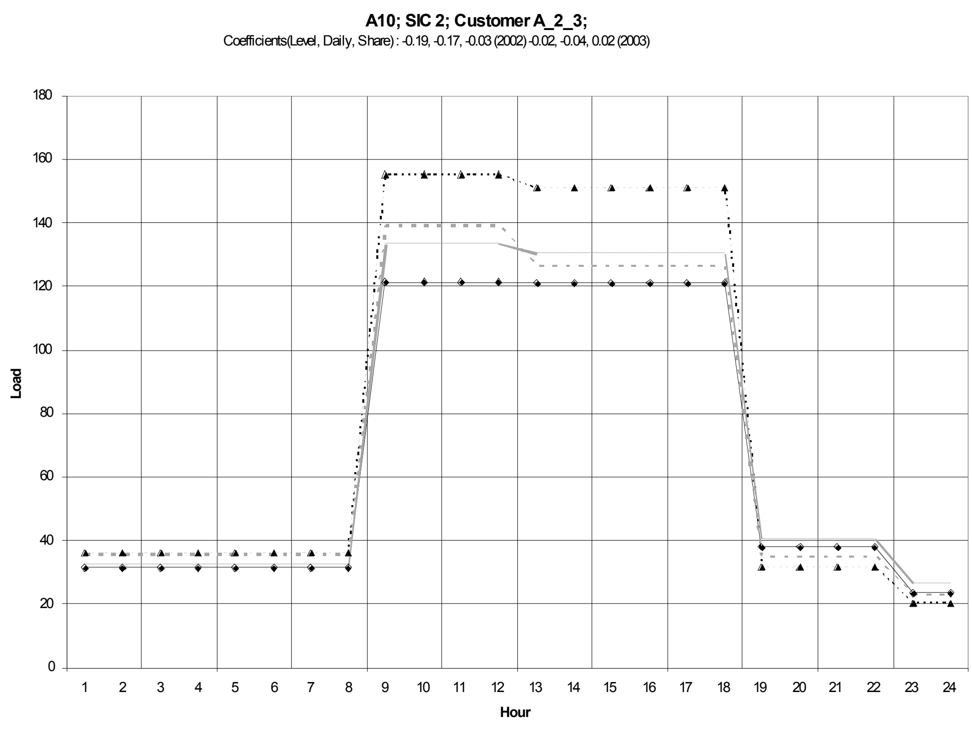
Interestingly, calculations of potential bill savings from a range of summer peak load reductions in the face of PG&E's standard TOU tariffs, presented in Table 6.2, indicate bill savings in the range of those examined in the recent WG2 evaluation—1 to 5 percent. Thus, the findings from the present study indicate that some 10 to 20 percent or more of customers have already decided that bill savings of those magnitudes are sufficient incentive to take actions to reduce their peak load during the summer months, producing an aggregate peak load reduction (27.1 MW) that represents a significant portion of the amount suggested in the WG2 report as a reasonable potential for DR programs. However, these findings also suggest one possible reason for the minimal response to the CPP and DBP discussed in that report. That is, the very type of customers that should be attracted to such programs may have already exhausted their potential peak period load response, and would have trouble squeezing out any more load response from their operations, particularly in return for payments (*e.g.*, $0.15/kWh) that are less than the effective TOU prices they already face.[14]

The results of this study do indicate, however, that a substantial DR potential exists among the class of customers examined (customer accounts of 200 to 5,000 kW in SIC 2 through7) if a DR program design, in conjunction with a tariff redesign could allow these customers access to lower cost power during summer peak periods when wholesale costs are relatively low, in return for facing prices even higher than the standard tariffs' peak period prices only on occasional days of high wholesale energy costs. This essentially describes a form of CPP program with a substantial differential between the critical peak and normal peak period prices. Customers could then provide the summer peak load response that they already endure for the entire summer, but for only the relatively few days for which capacity constraints may exist in the state.

[14] PG&E, SCE and SDG&E have all reduced their tariff prices from the levels that were in place during the 2001 to 2003 period of analysis of this study.

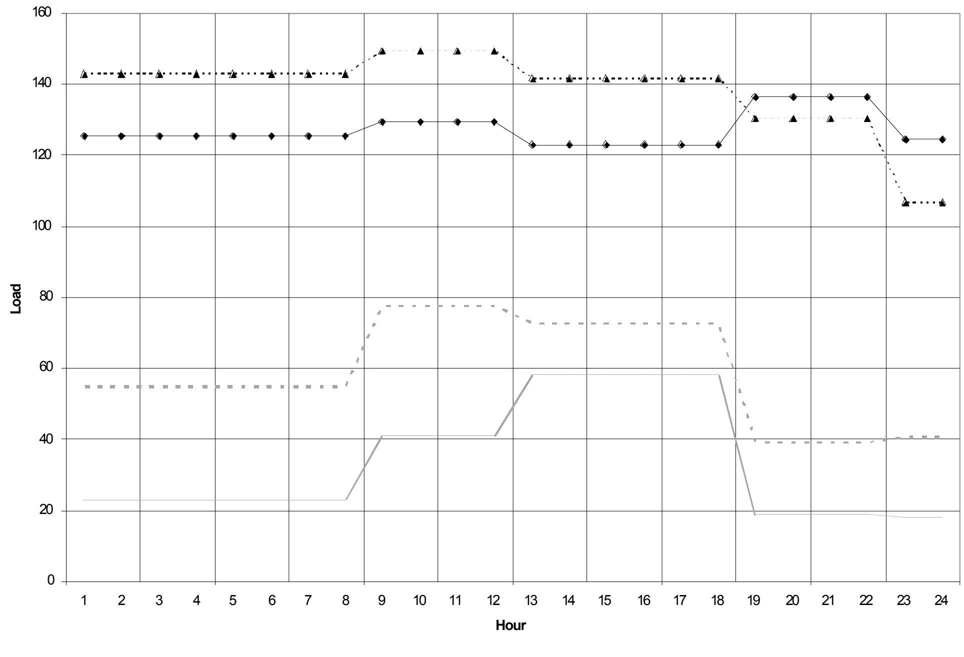
Appendix B.1 Selected A10 Customer Load Profiles





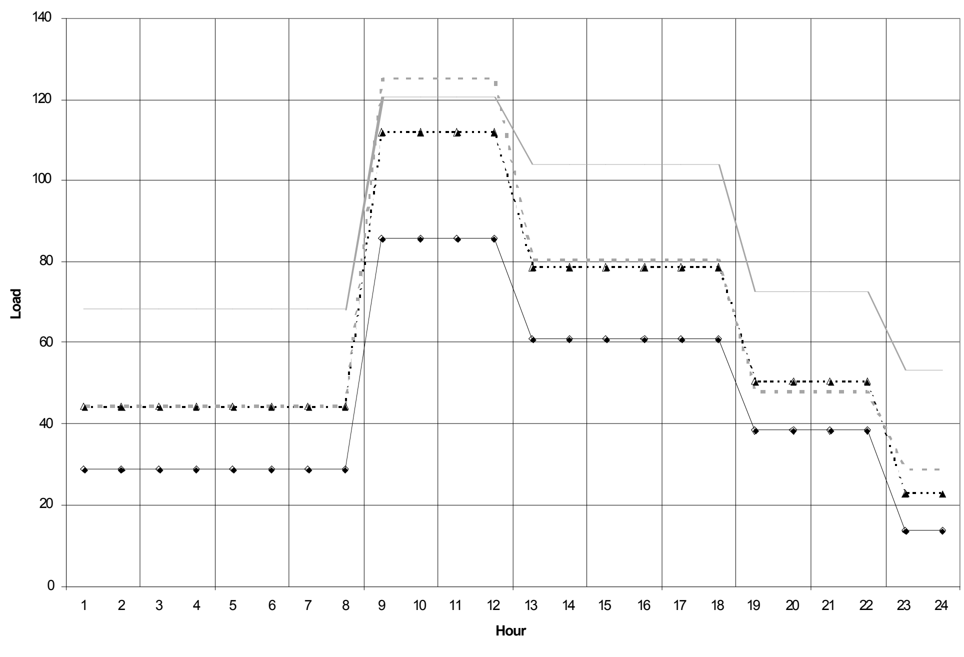
A10; SIC 2; Customer A_2_4;

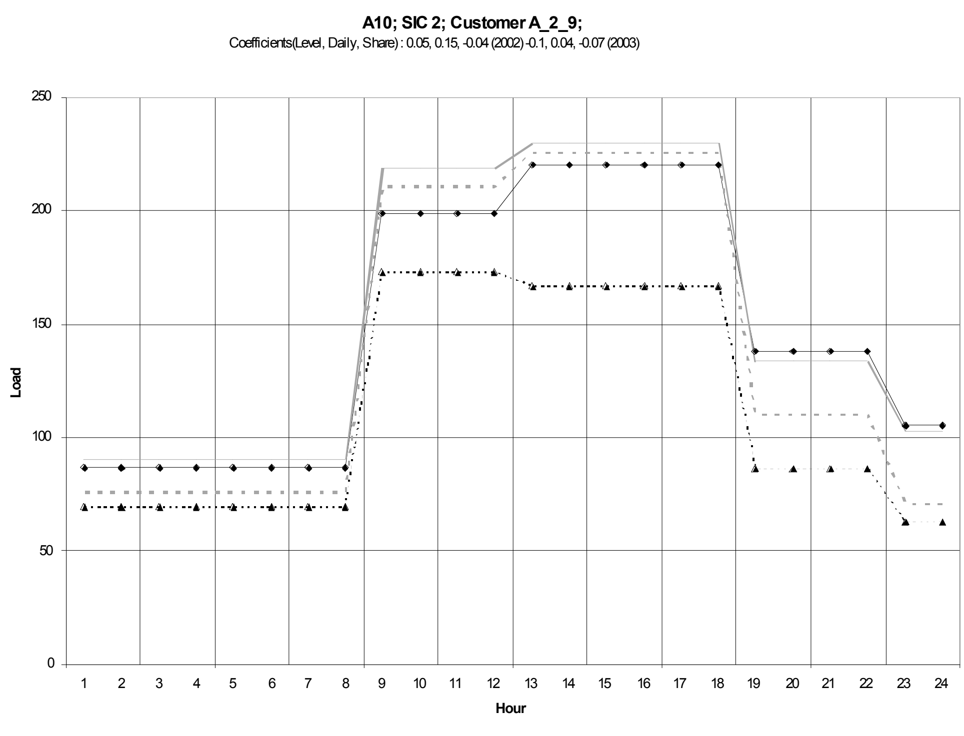
Coefficients(Level, Daily, Share) : -0.03, -0.07, -0.09 (2002) 0.13, 0.09, 0.08 (2003)



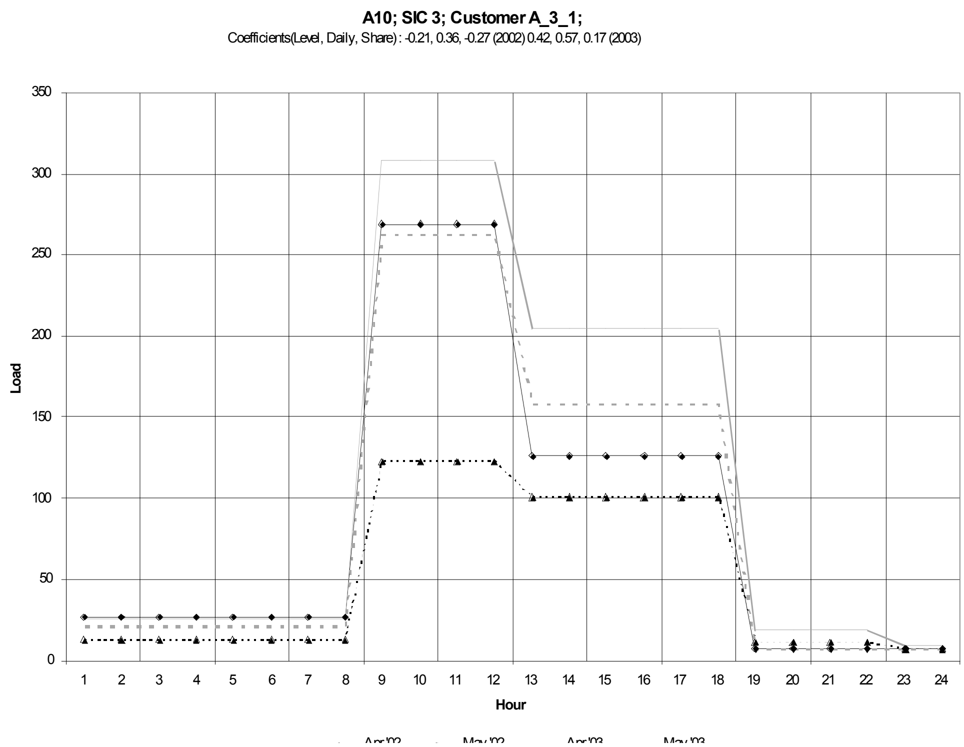
A10; SIC 2; Customer A_2_5;

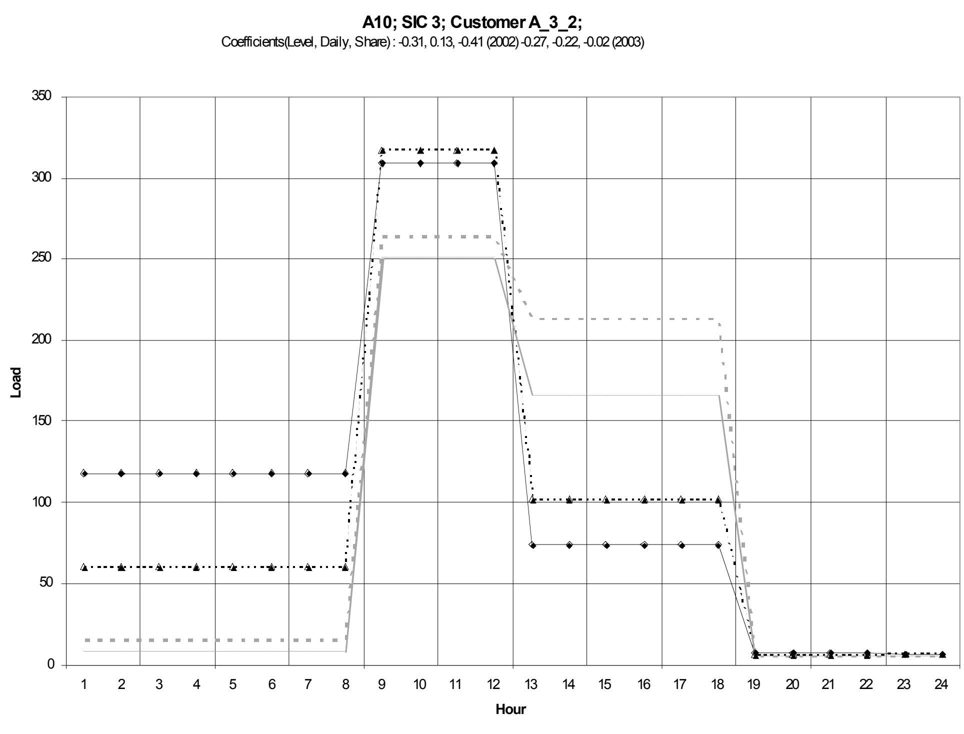
Coefficients(Level, Daily, Share) : -0.25, -0.28, -0.03 (2002) 0.04, 0.08, -0.03 (2003)

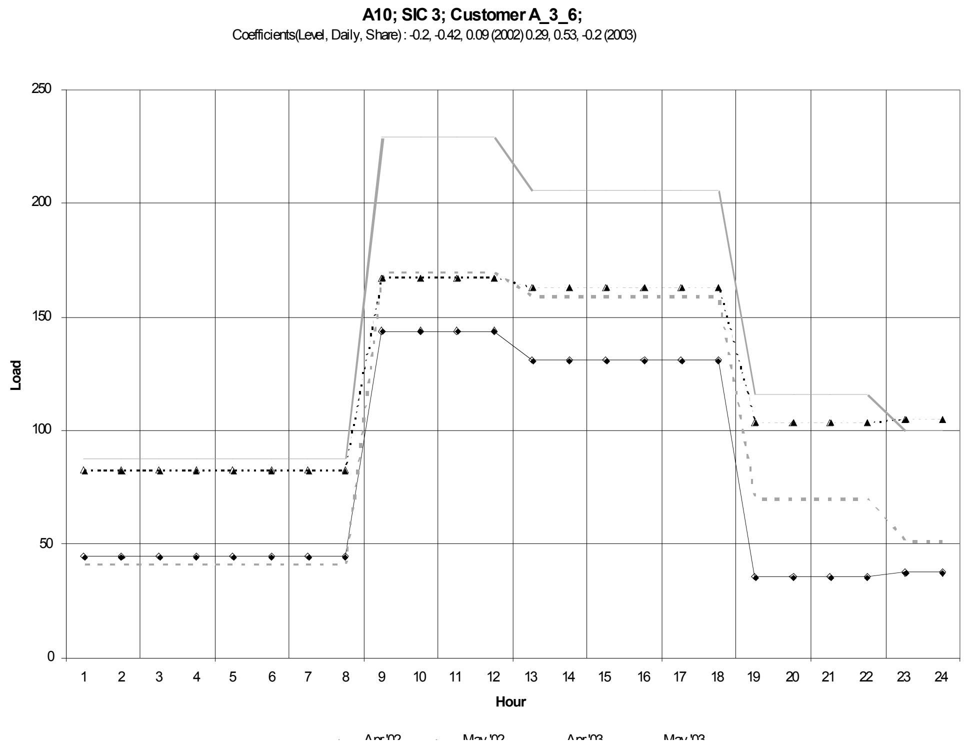




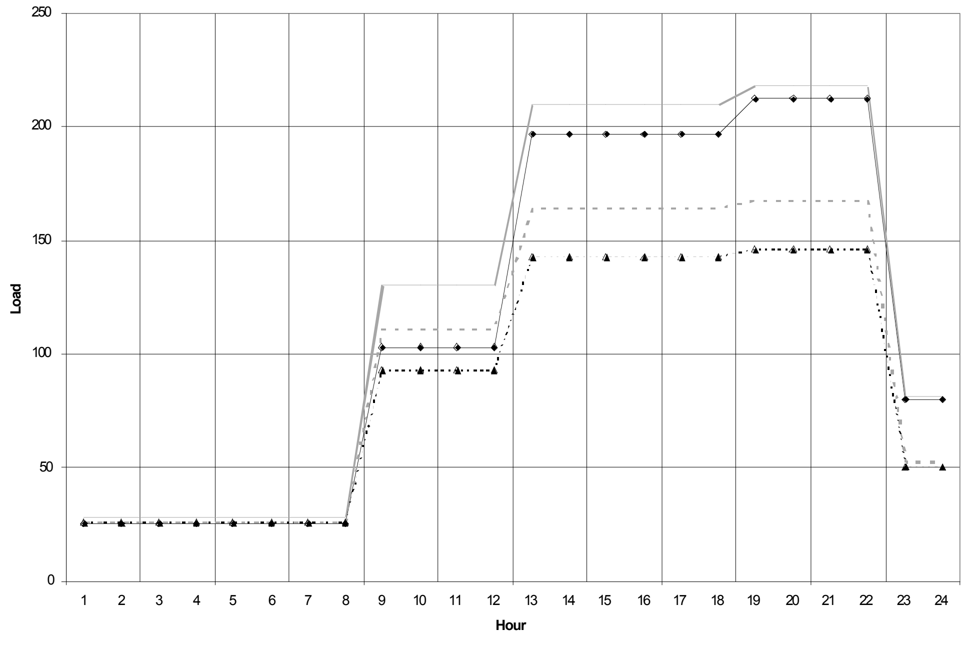
A10; SIC 2; Customer A_2_9;
Coefficients(Level, Daily, Share) : 0.05, 0.15, -0.04 (2002) -0.1, 0.04, -0.07 (2003)
Load
Hour


A10; SIC 3; Customer A_3_1;
Coefficients(Level, Daily, Share) : -0.21, 0.36, -0.27 (2002) 0.42, 0.57, 0.17 (2003)
Load
0
50
100
150
200
250
300
350
Hour
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

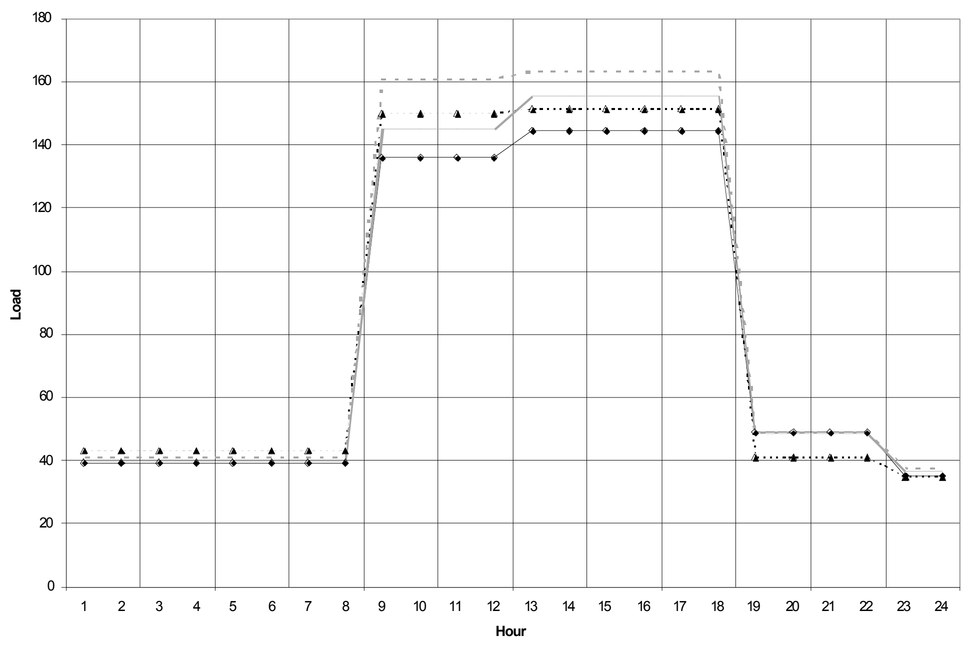

A10; SIC 3; Customer A_3_2;
Coefficients(Level, Daily, Share) : -0.31, 0.13, -0.41 (2002) -0.27, -0.22, -0.02 (2003)
Load
0
50
100
150
200
250
300
350
Hour
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

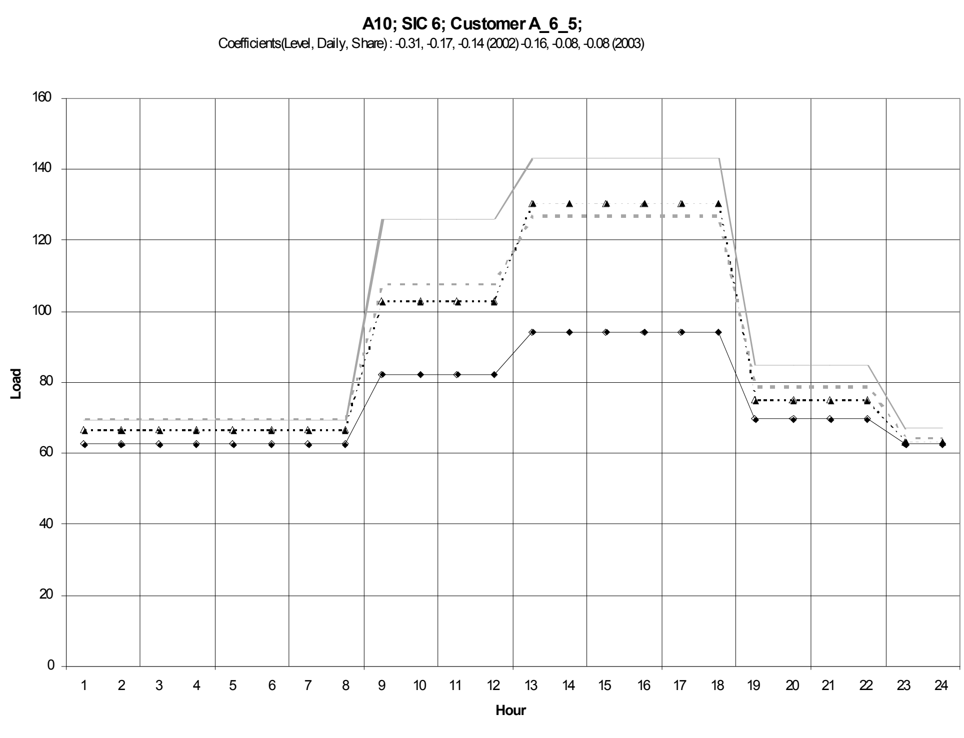

A10; SIC 3; Customer A_3_6;
Coefficients(Level, Daily, Share) : -0.2, -0.42, 0.09 (2002) 0.29, 0.53, -0.2 (2003)
Load
0
50
100
150
200
250
Hour
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Apr'02
May'02
Apr'03
May'03

A10; SIC 5; Customer A_5_2;
Coefficients(Level, Daily, Share) : 0.03, 0.13, 0 (2002) 0.04, 0.06, -0.06 (2003)

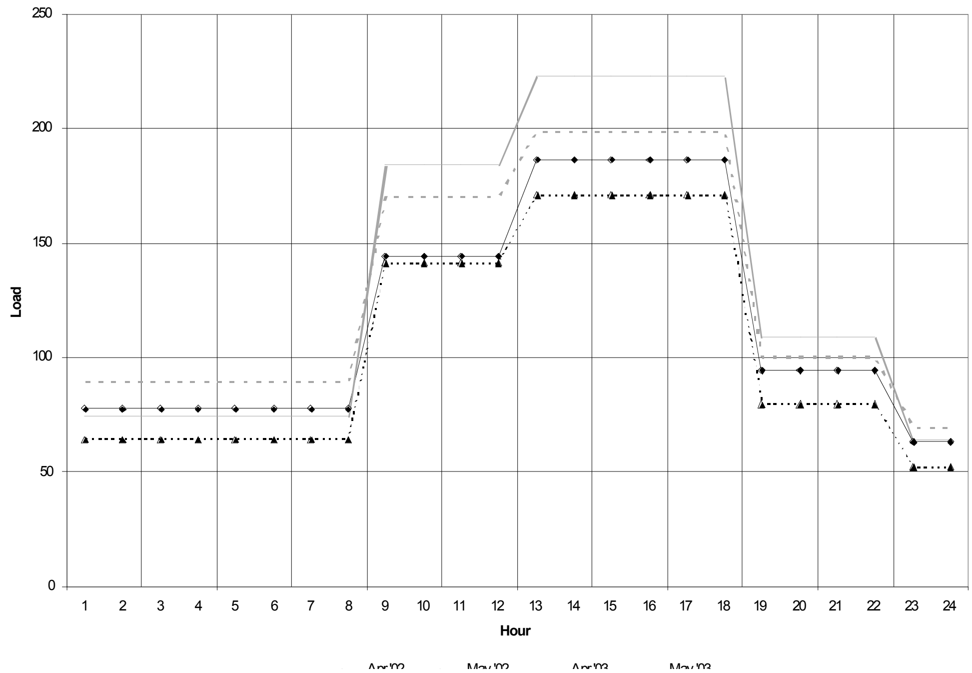


A10; SIC 6; Customer A_6_3;
Coefficients(Level, Daily, Share) : -0.09, -0.06, 0 (2002) 0.02, 0, 0.01 (2003)

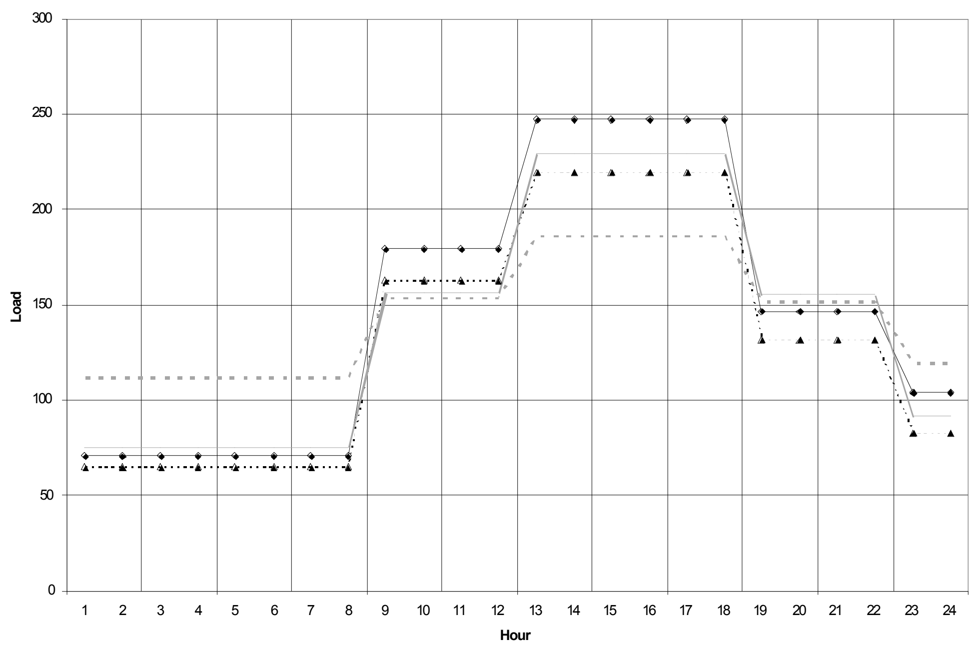


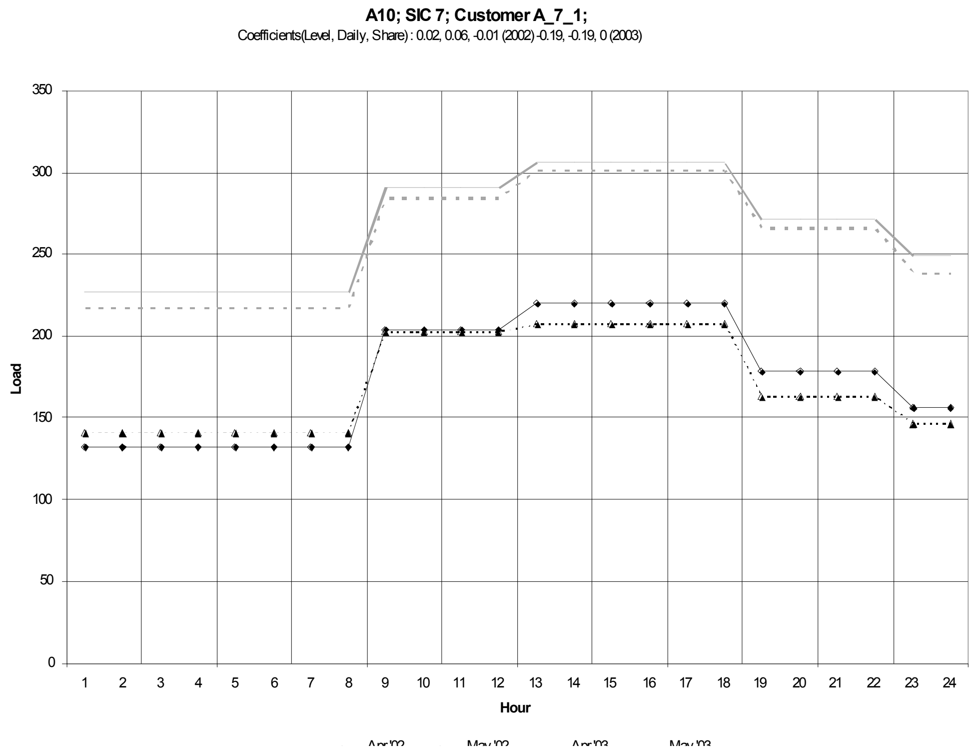

A10; SIC 6; Customer A_6_5;
Coefficients(Level, Daily, Share) : -0.31, -0.17, -0.14 (2002) -0.16, -0.08, -0.08 (2003)
Load
160
140
120
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr'02
May'02
Apr'03
May'03

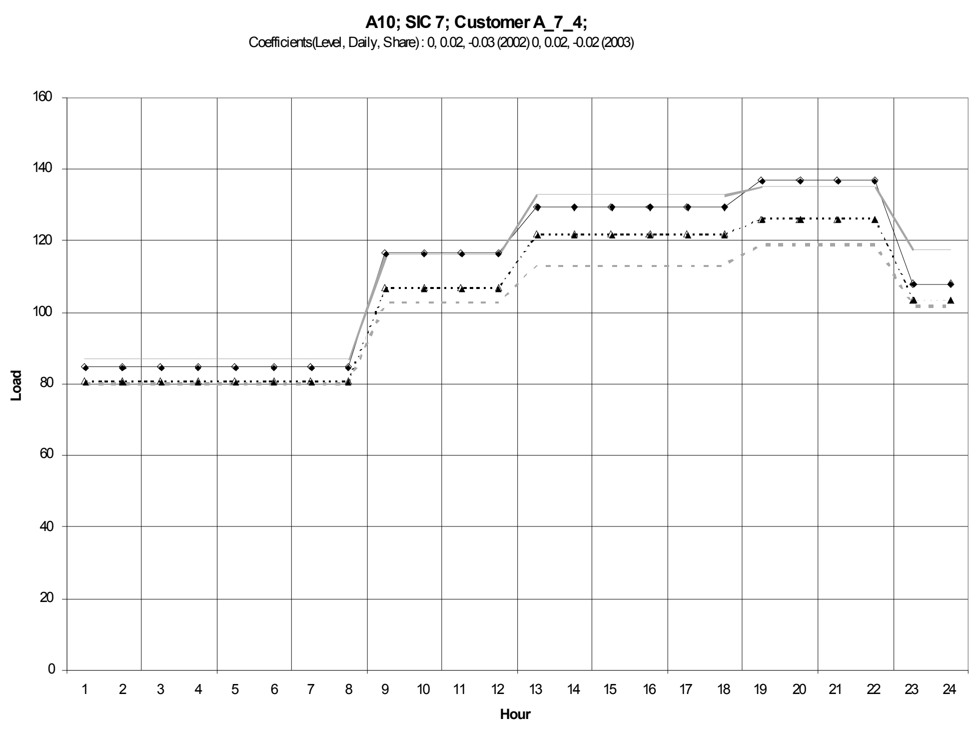
A10; SIC 6; Customer A_6_7;
Coefficients(Level, Daily, Share) : -0.02, 0.07, -0.06 (2002) -0.01, -0.04, 0.03 (2003)



A10; SIC 6; Customer A_6_9;
Coefficients(Level, Daily, Share) : 0.17, 0.12, 0.01 (2002) 0.07, -0.11, 0.2 (2003)

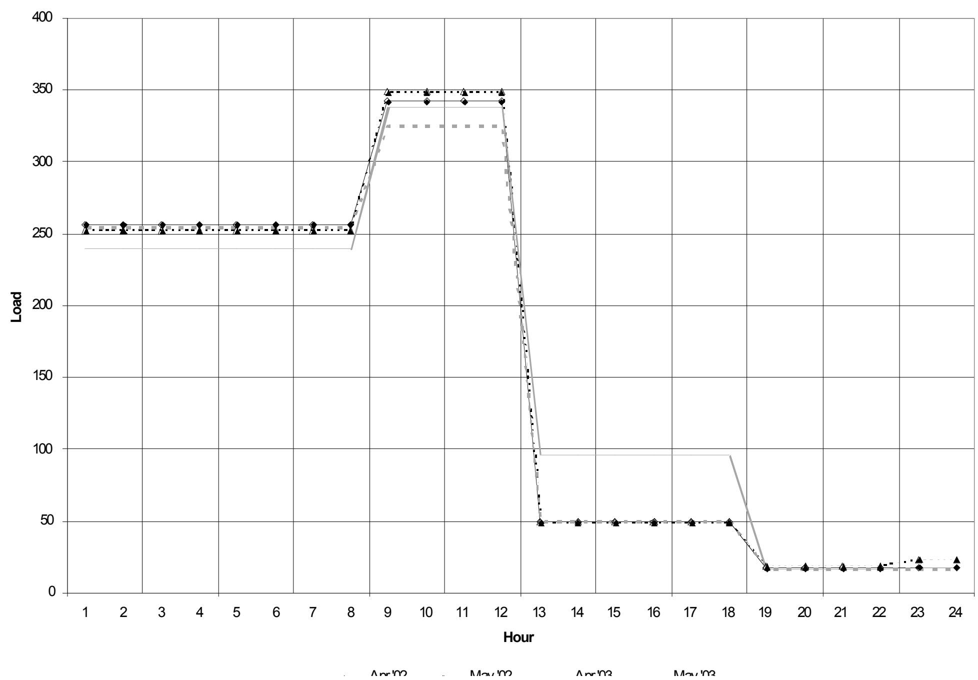



A10; SIC 7; Customer A_7_1;
Coefficients(Level, Daily, Share) : 0.02, 0.06, -0.01 (2002) -0.19, -0.19, 0 (2003)
Load
Hour
350
300
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

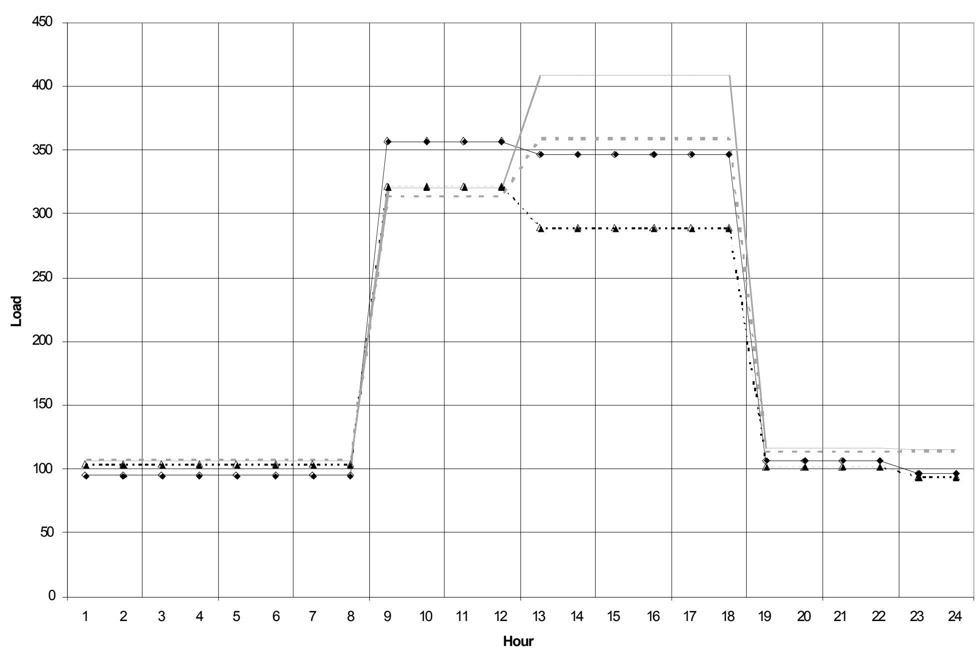

A10; SIC 7; Customer A_7_4;
Coefficients(Level, Daily, Share) : 0, 0.02, -0.03 (2002) 0, 0.02, -0.02 (2003)
Load
Hour
160
140
120
100
80
60
40
20
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

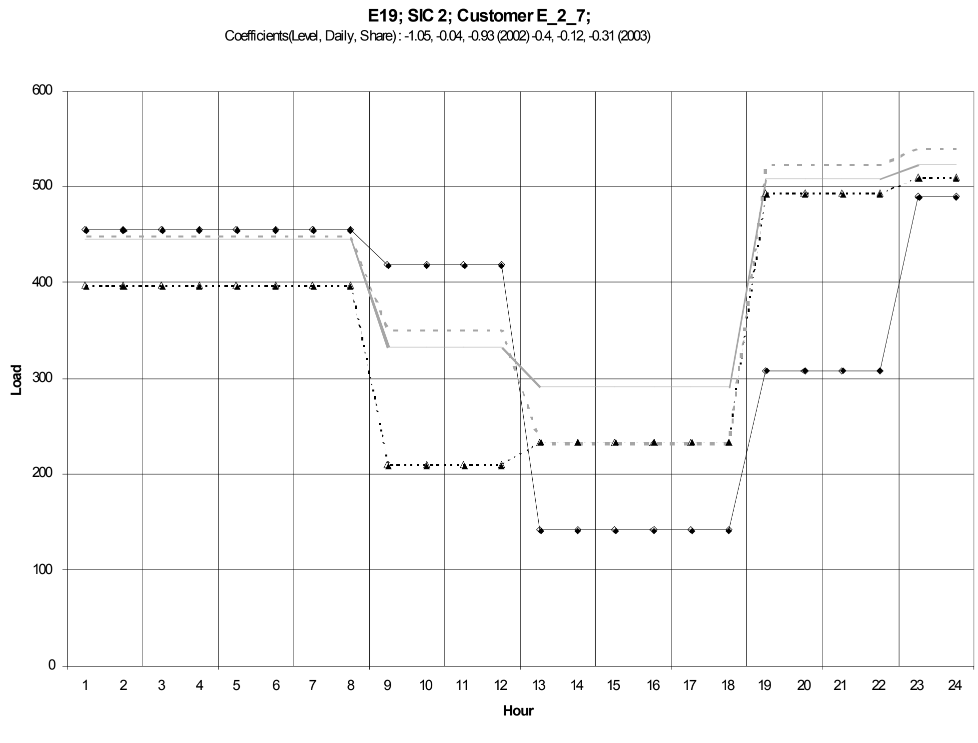
Appendix B.2 Selected E19 Customer Load Profiles

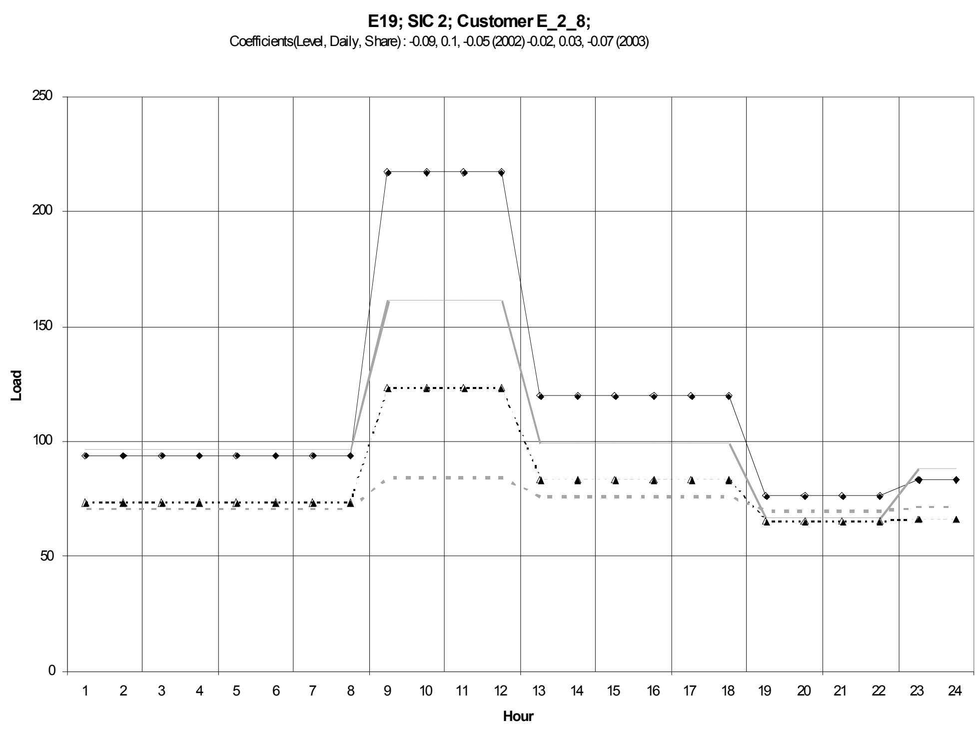
E19; SIC 2; Customer E_2_1;
Coefficients(Level, Daily, Share) : -0.64, -0.04, -0.58 (2002) 0.17, 0, 0.16 (2003)



E19; SIC 2; Customer E_2_4;
Coefficients(Level, Daily, Share) : -0.45, -0.25, 0.26 (2002) -0.37, -0.21, 0.32 (2003)

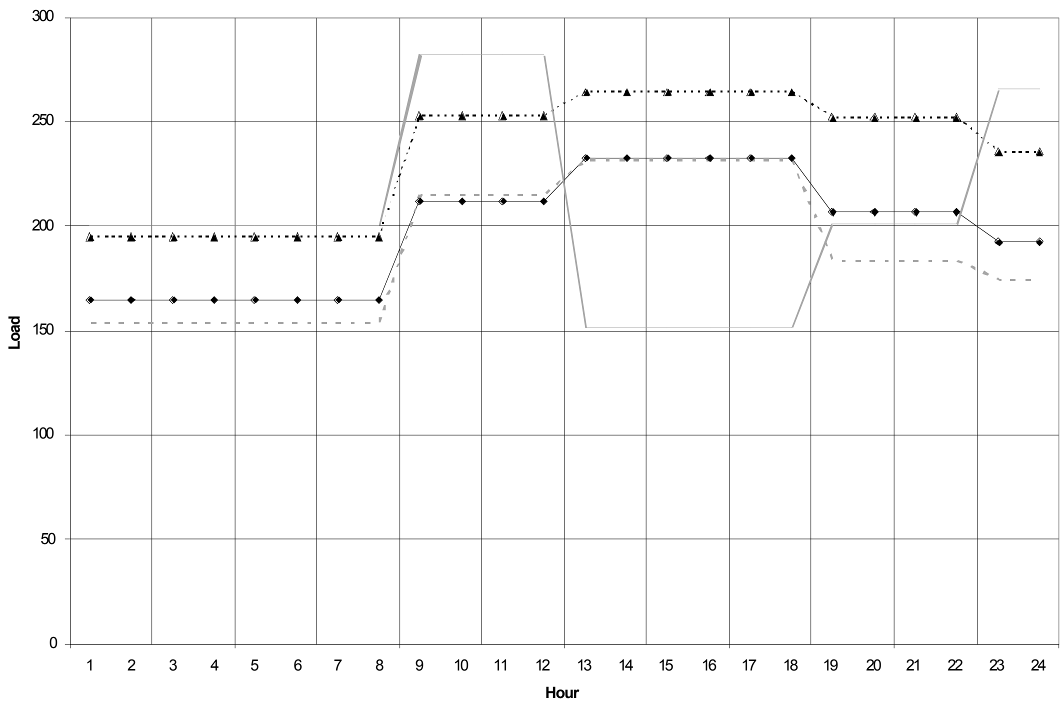



E19; SIC 2; Customer E_2_7;
Coefficients(Level, Daily, Share) : -1.05, -0.04, -0.93 (2002) -0.4, -0.12, -0.31 (2003)
Load
Hour


E19; SIC 2; Customer E_2_8;
Coefficients(Level, Daily, Share) : -0.09, 0.1, -0.05 (2002) -0.02, 0.03, -0.07 (2003)
Load
Hour

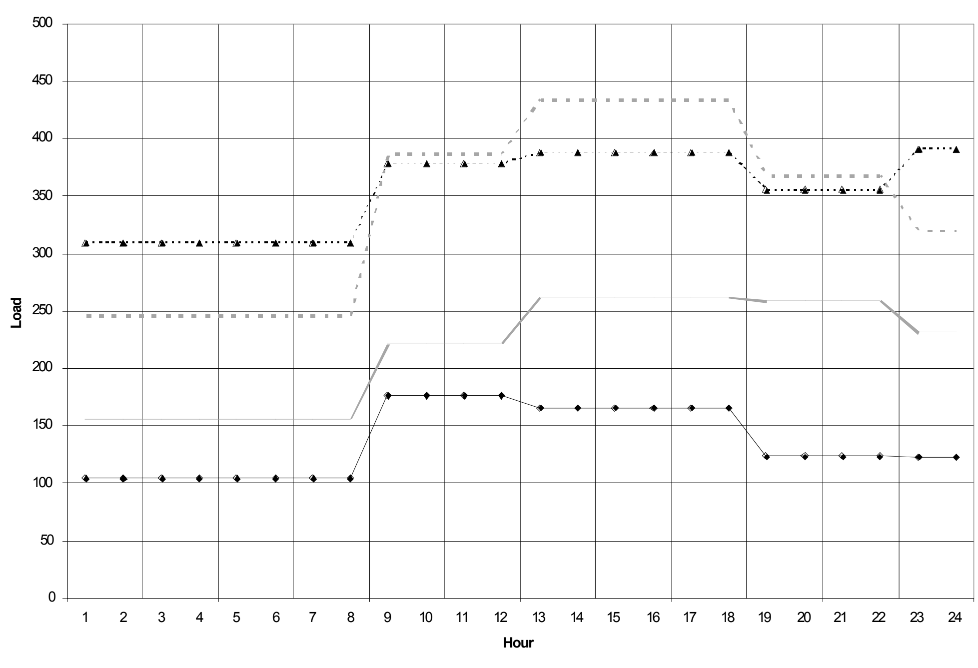
E19; SIC 2; Customer E_2_14;

Coefficients(Level, Daily, Share) : -0.49, -0.27, 0 (2002) -0.71, -0.16, -0.52 (2003)

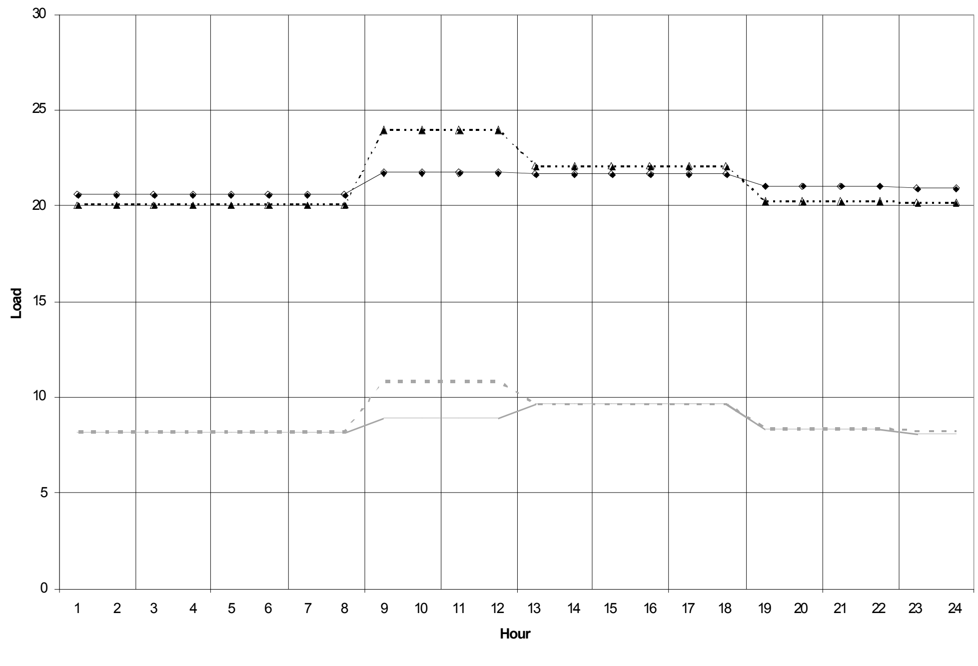


E19; SIC 2; Customer E_2_15;

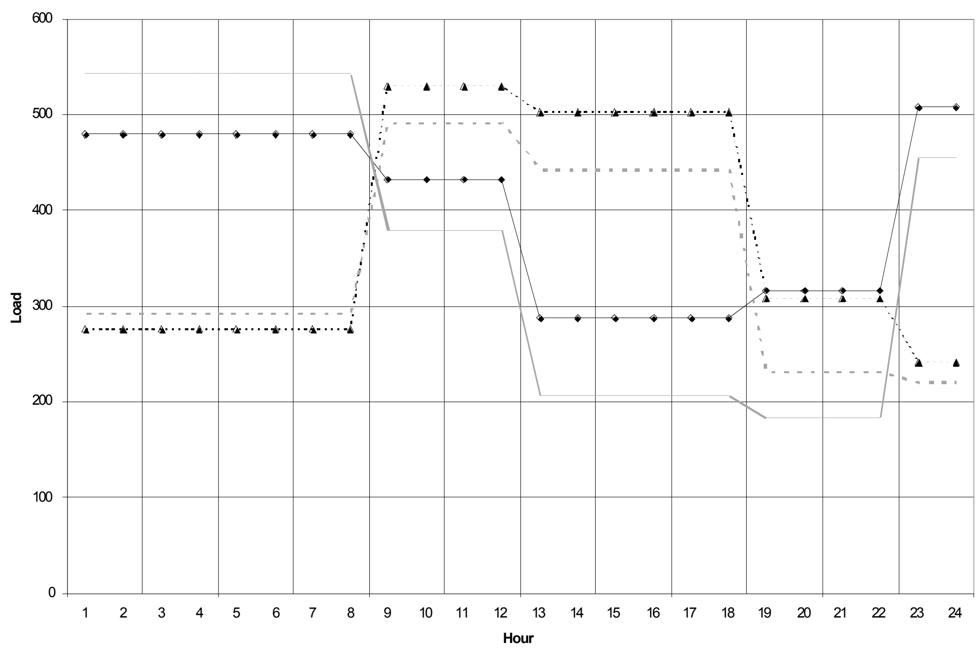
Coefficients(Level, Daily, Share) : -1.48, -1.7, 0.39 (2002) -1.45, -1.5, 0.24 (2003)



E19; SIC 2; Customer E_2_17;
Coefficients(Level, Daily, Share) : 0.08, -0.06, -0.01 (2002) -0.02, 0.11, -0.05 (2003)

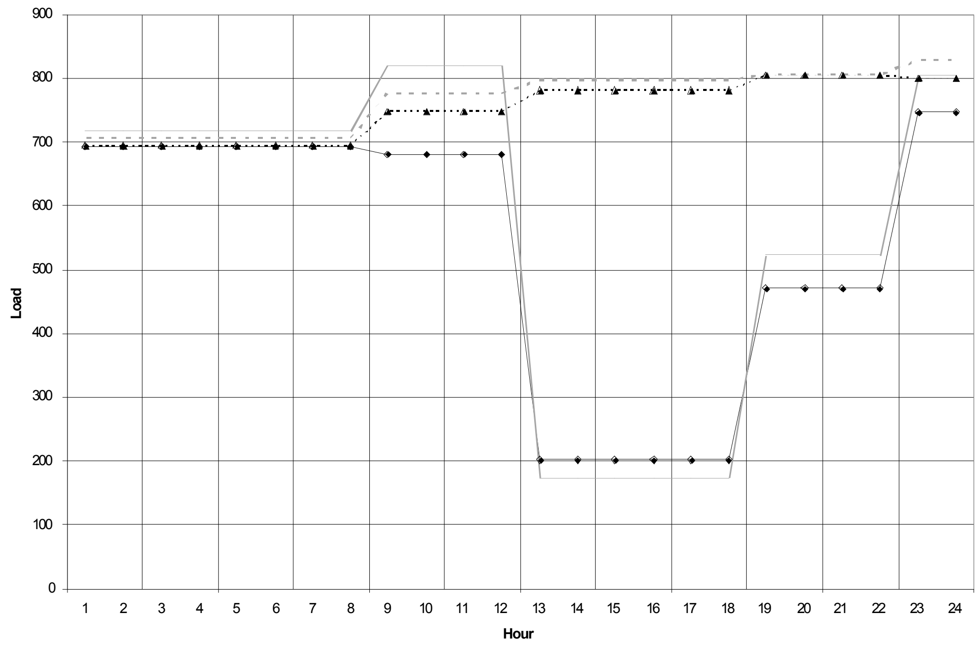


E19; SIC 2; Customer E_2_19;
Coefficients(Level, Daily, Share) : -0.1, 0.03, -0.12 (2002) -0.56, 0.02, -0.58 (2003)



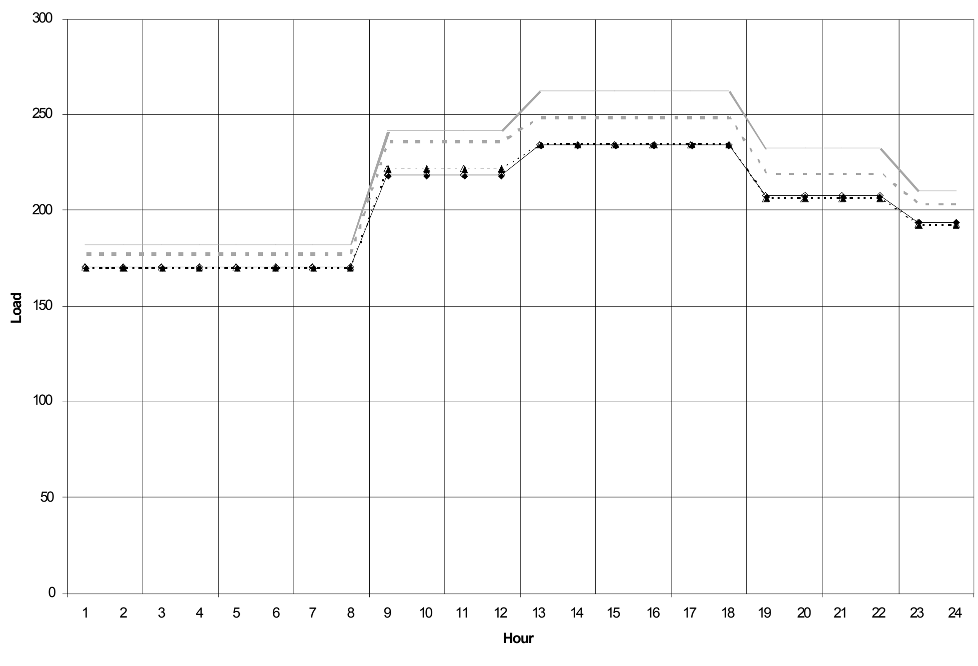
E19; SIC 2; Customer E_2_20;

Coefficients(Level, Daily, Share) : -1.04, -0.15, -0.82 (2002) -1.62, -0.32, -1.3 (2003)

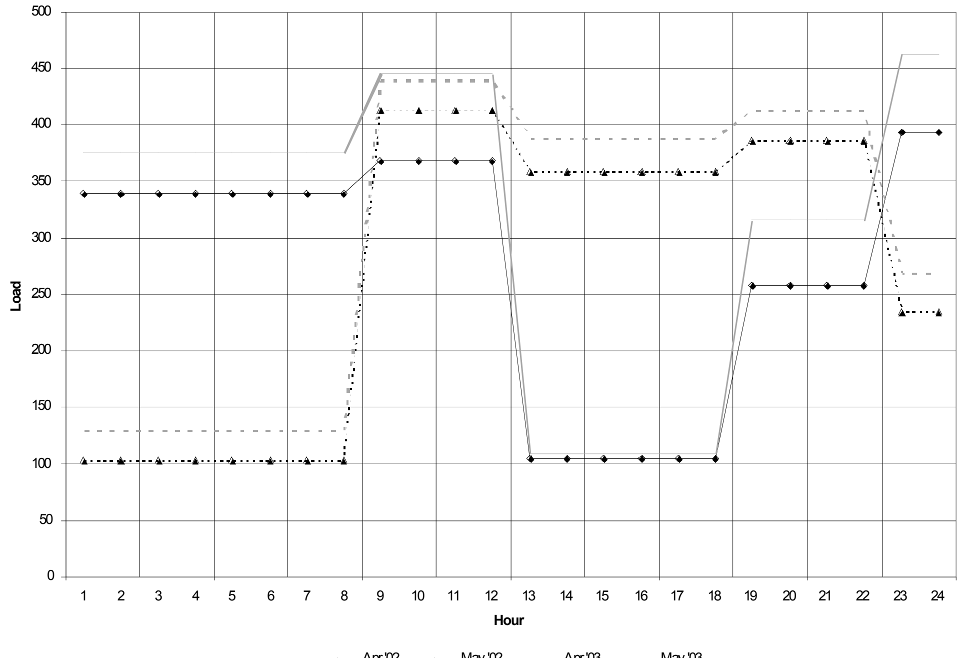


E19; SIC 2; Customer E_2_21;

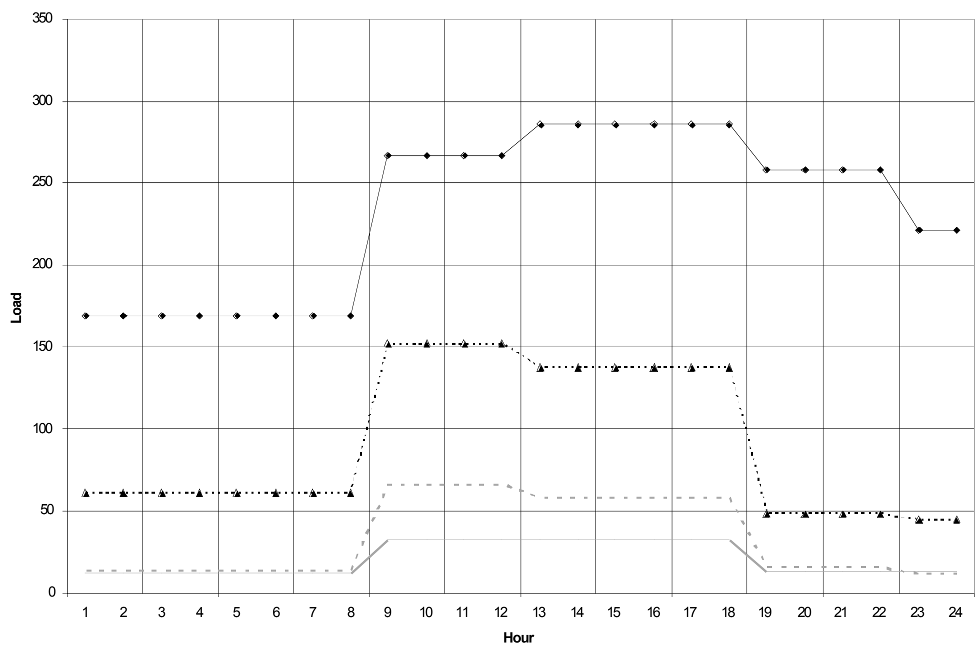
Coefficients(Level, Daily, Share) : -0.06, -0.05, 0.01 (2002) 0.04, 0.04, 0 (2003)



E19; SIC 3; Customer E_3_2;
Coefficients(Level, Daily, Share) : -0.54, -0.04, -0.46 (2002) -1.09, 0.05, -1.15 (2003)

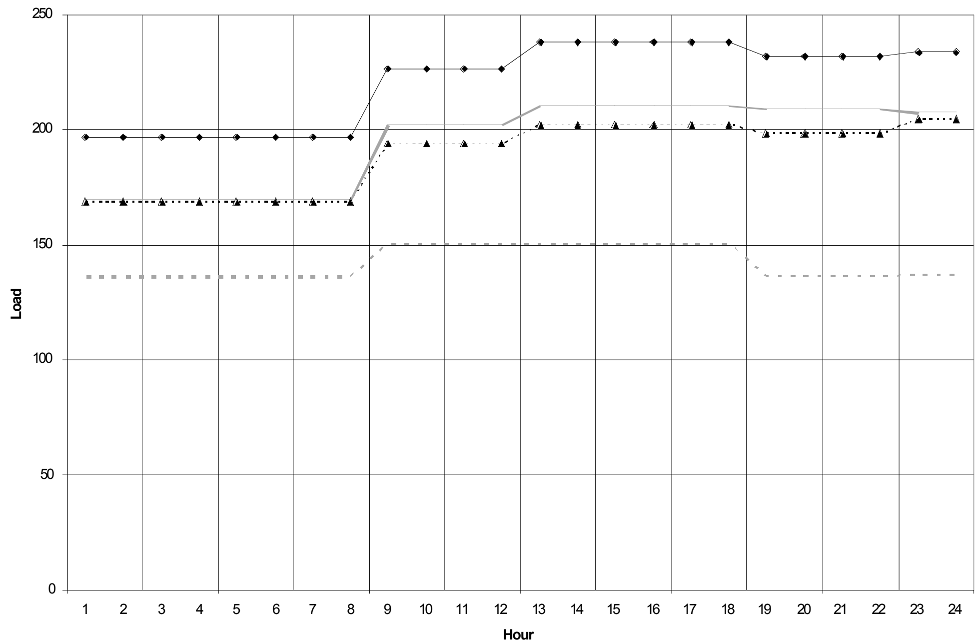


E19; SIC 3; Customer E_3_4;
Coefficients(Level, Daily, Share) : 0.46, -0.53, 0.04 (2002) 0.48, -0.22, 0.26 (2003)



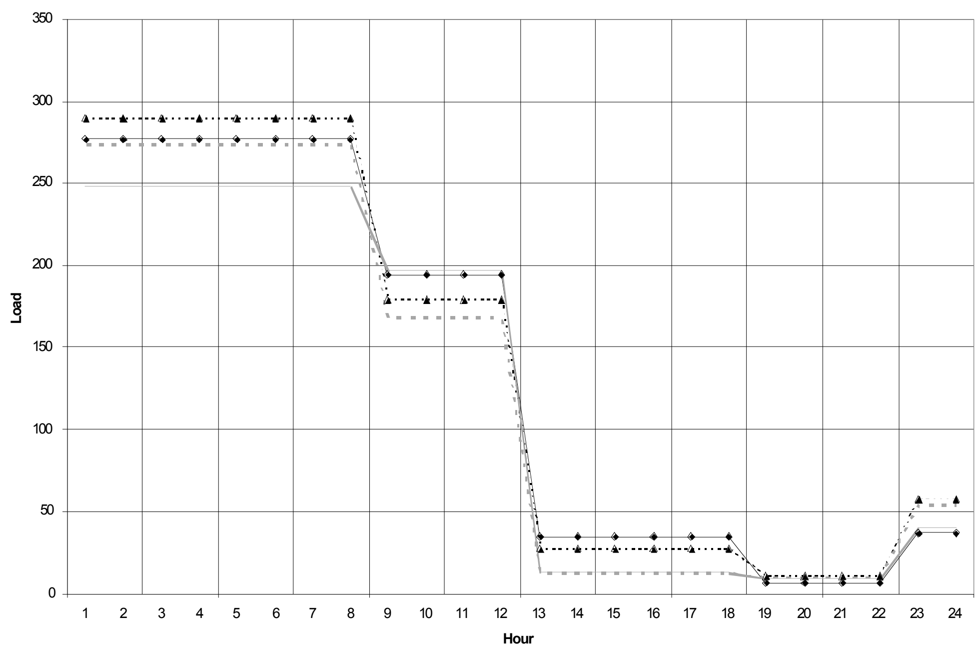
E19; SIC 3; Customer E_3_5;

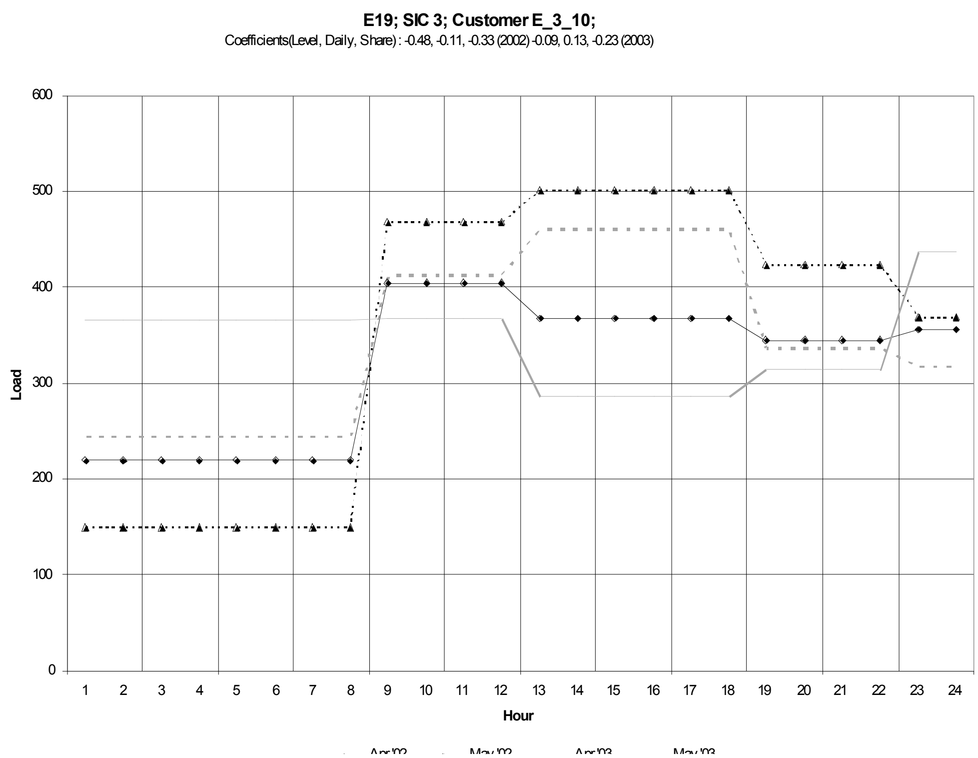
Coefficients(Level, Daily, Share) : 0.36, 0.23, 0.06 (2002) 0.59, 0.45, 0.16 (2003)



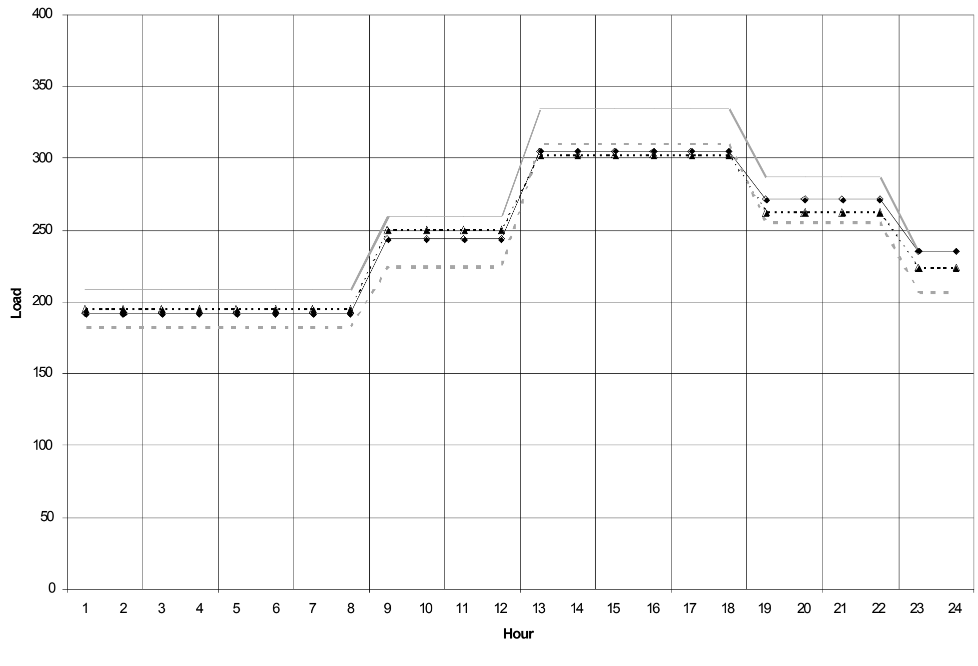
E19; SIC 3; Customer E_3_6;

Coefficients(Level, Daily, Share) : -0.75, 0.32, -0.95 (2002) -0.29, 0.23, -0.37 (2003)

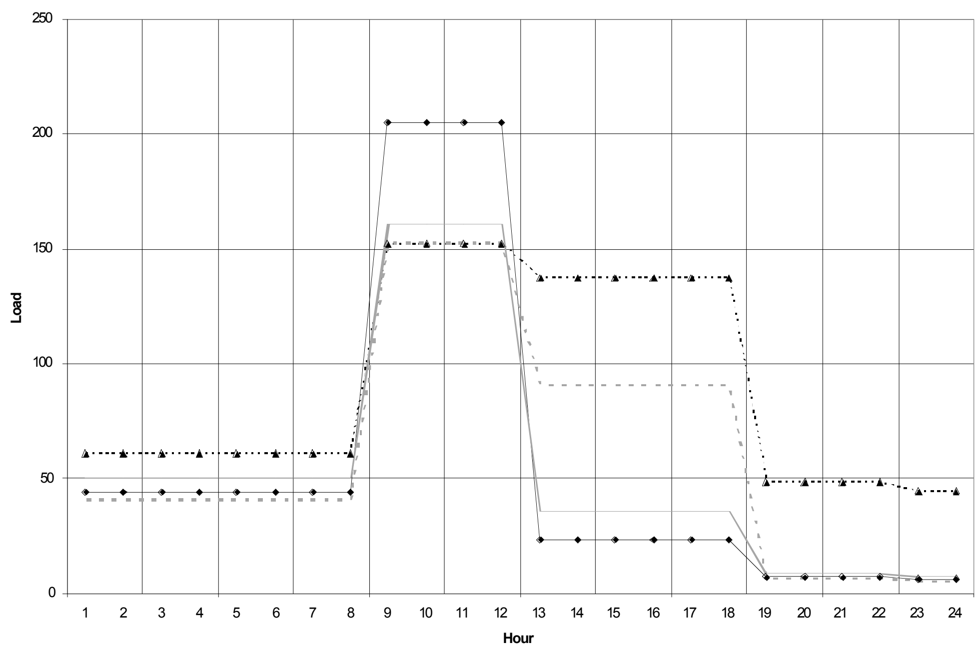


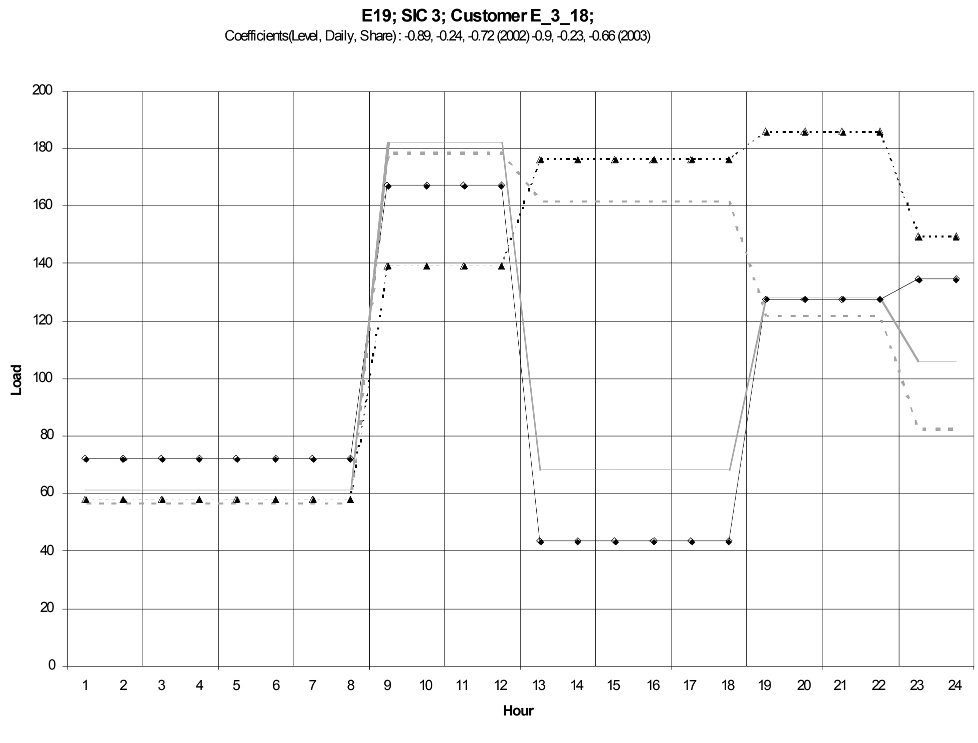

E19; SIC 3; Customer E_3_10;
Coefficients(Level, Daily, Share) : -0.48, -0.11, -0.33 (2002) -0.09, 0.13, -0.23 (2003)
600
500
400
300
200
100
0
Load
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour
Apr '02
May '02
Apr '03
May '03

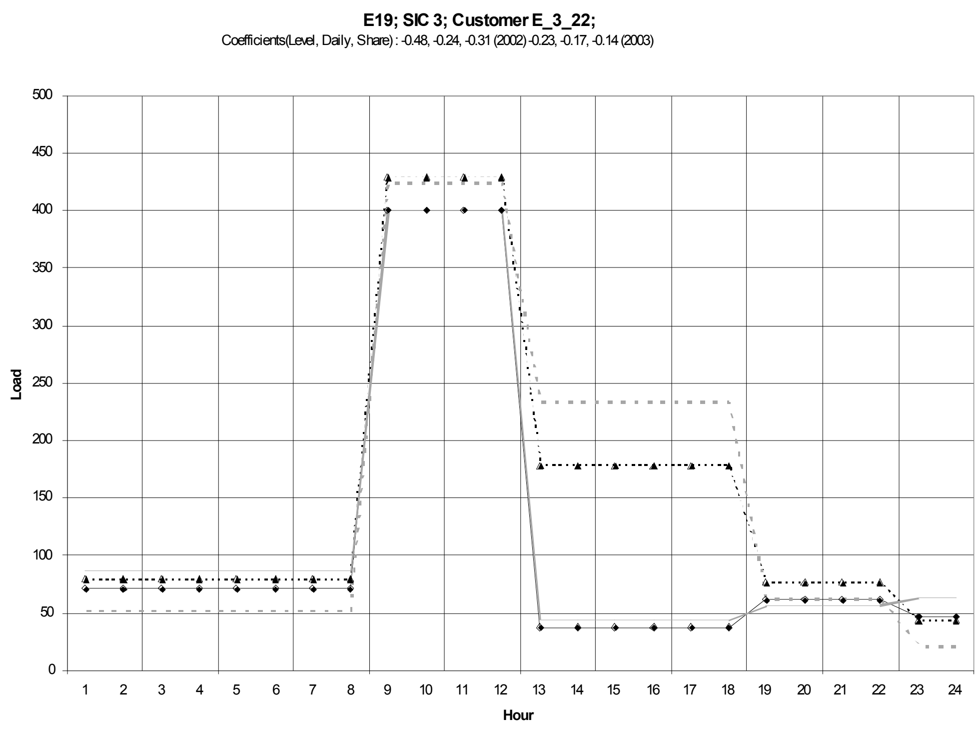
E19; SIC 3; Customer E_3_14;
Coefficients(Level, Daily, Share) : 0.03, 0.01, 0.02 (2002) 0, 0.01, -0.01 (2003)



E19; SIC 3; Customer E_3_16;
Coefficients(Level, Daily, Share) : 0.18, 0.56, 0.15 (2002) -0.4, -0.07, -0.09 (2003)

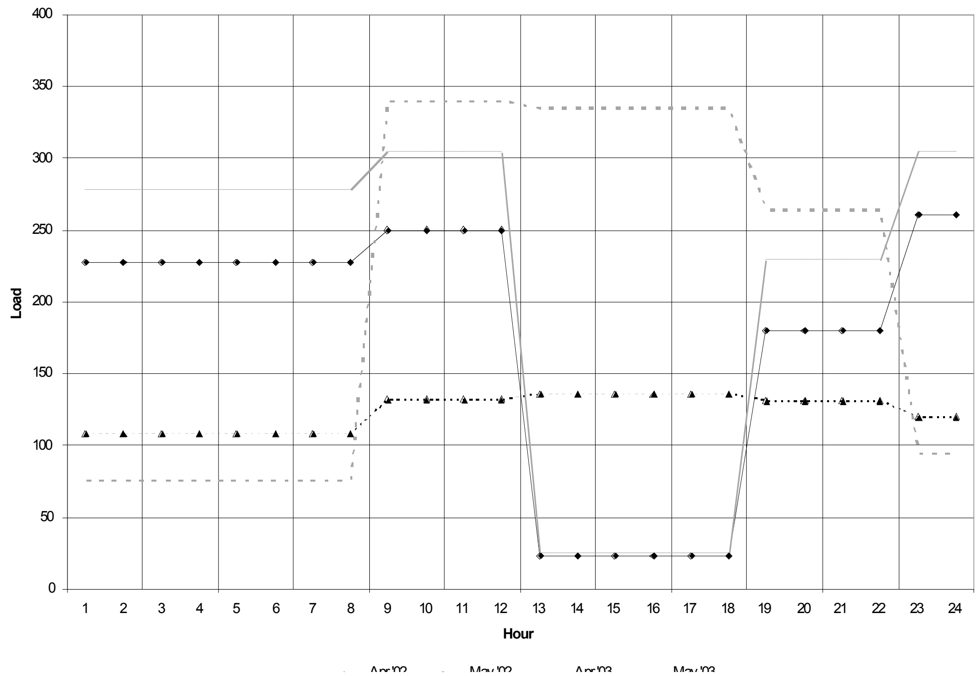



E19; SIC 3; Customer E_3_18;
Coefficients(Level, Daily, Share) : -0.89, -0.24, -0.72 (2002) -0.9, -0.23, -0.66 (2003)
Load
Hour


E19; SIC 3; Customer E_3_22;
Coefficients(Level, Daily, Share) : -0.48, -0.24, -0.31 (2002) -0.23, -0.17, -0.14 (2003)
Load
Hour

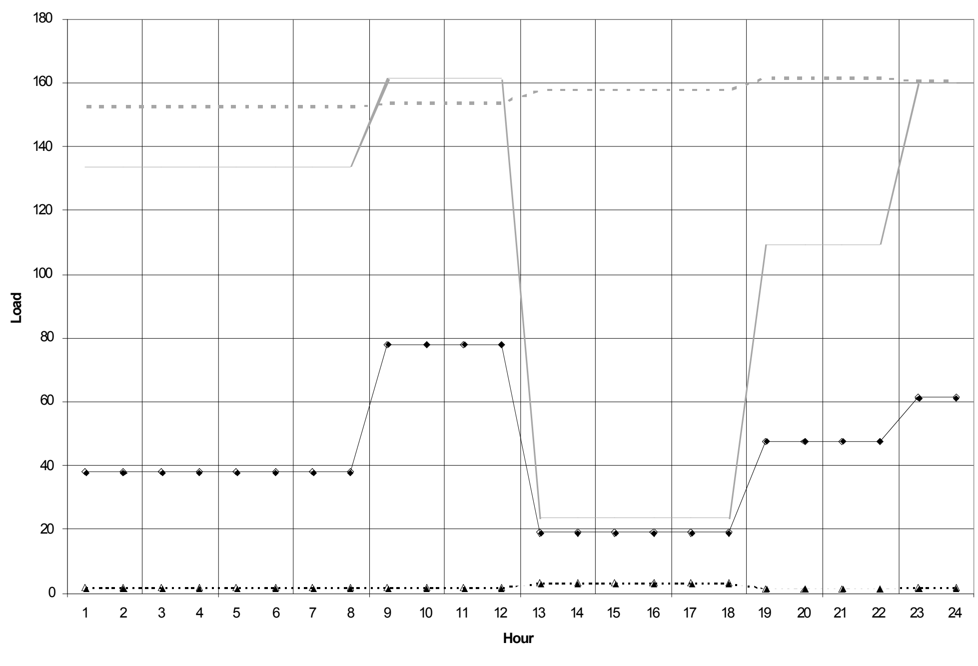
E19; SIC 4; Customer E_4_1;

Coefficients(Level, Daily, Share) : -0.43, 0.33, -0.72 (2002) -1.24, -0.01, -1.2 (2003)

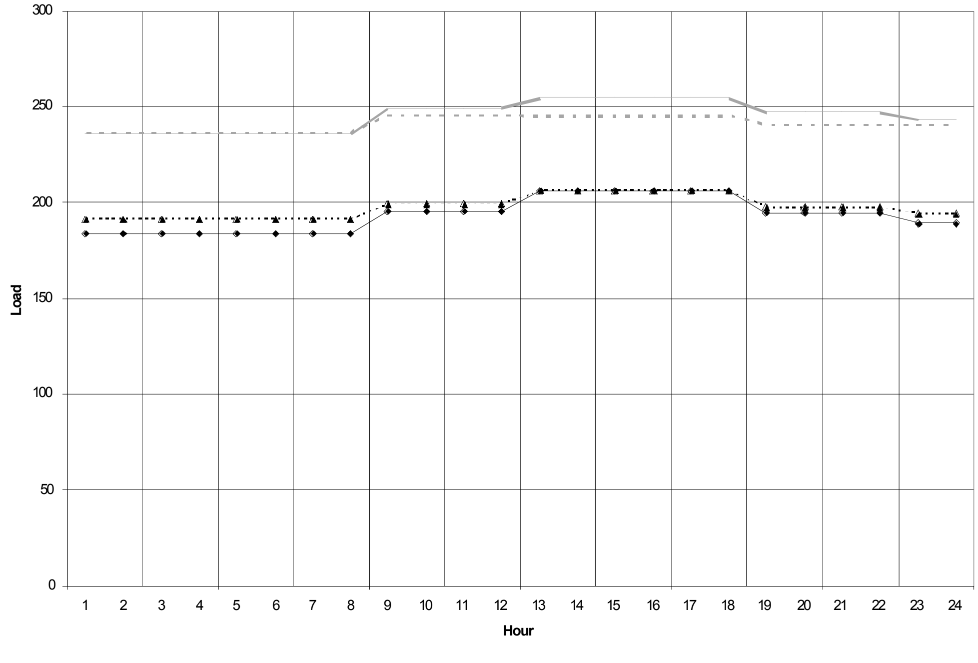


E19; SIC 4; Customer E_4_2;

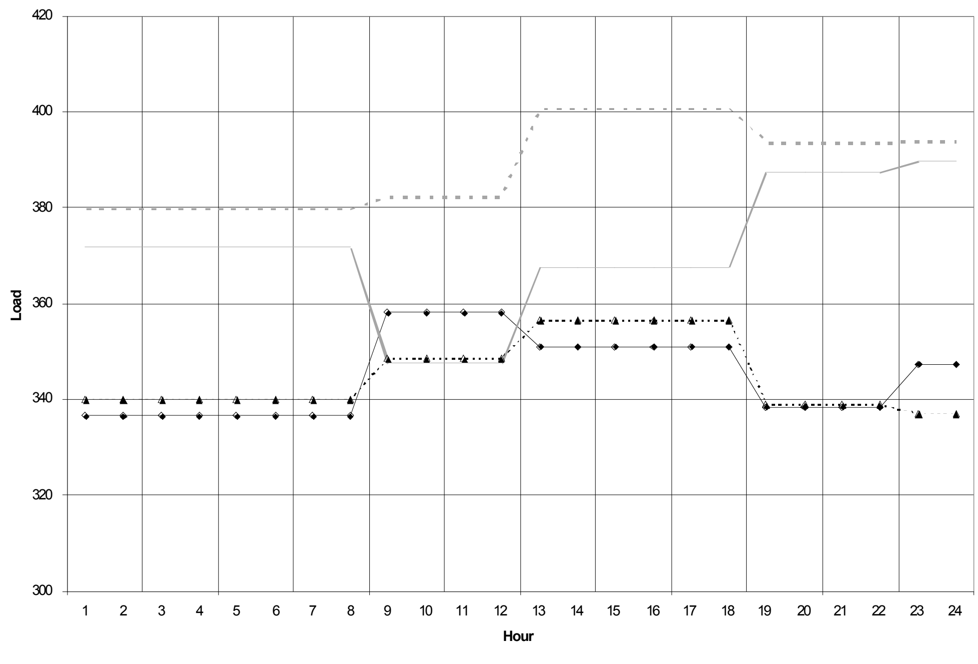
Coefficients(Level, Daily, Share) : 0.42, 1.55, 0.24 (2002) -2.36, -1.66, -1.18 (2003)



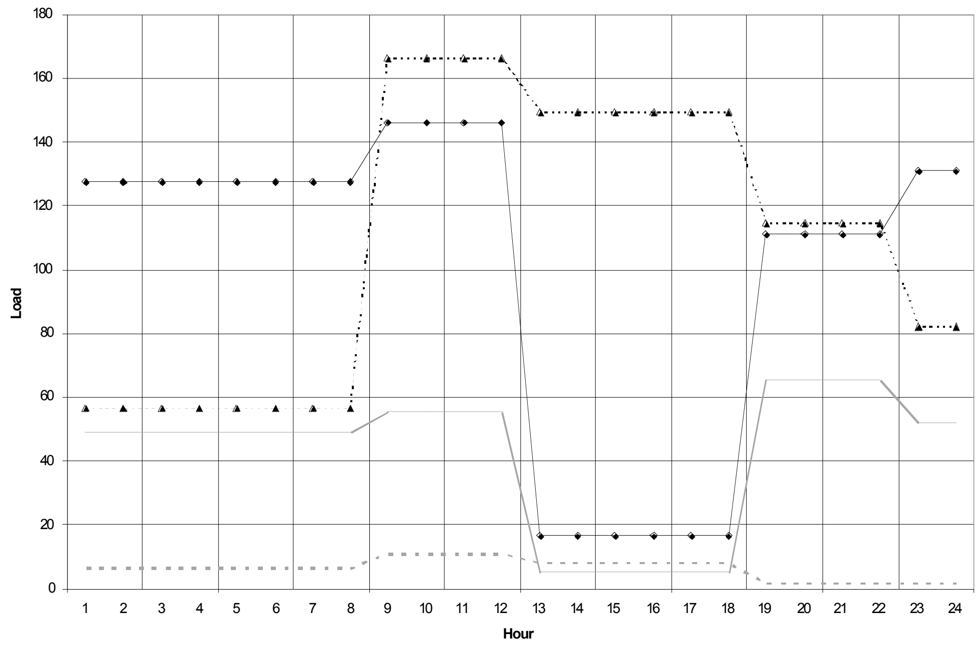
E19; SIC 4; Customer E_4_4;
Coefficients(Level, Daily, Share) : -0.21, -0.11, 0.06 (2002) -0.16, 0, 0.01 (2003)



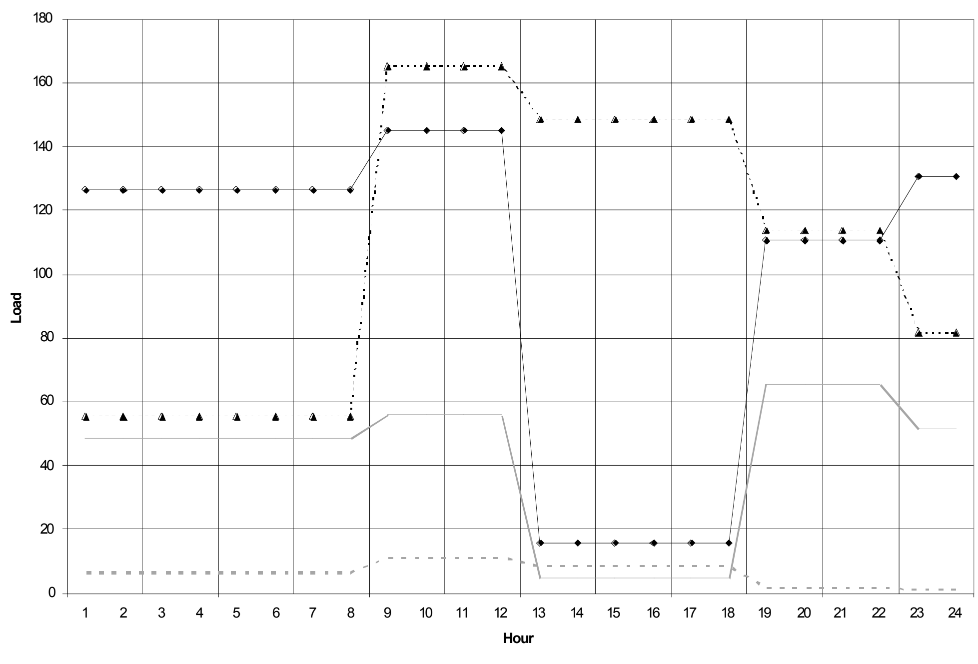
E19; SIC 4; Customer E_4_6;
Coefficients(Level, Daily, Share) : 0.01, 0.01, 0 (2002) -0.1, -0.03, -0.07 (2003)



E19; SIC 4; Customer E_4_8;
Coefficients(Level, Daily, Share) : -1.17, 0.01, -0.7 (2002) 0.26, 0.75, 0.03 (2003)

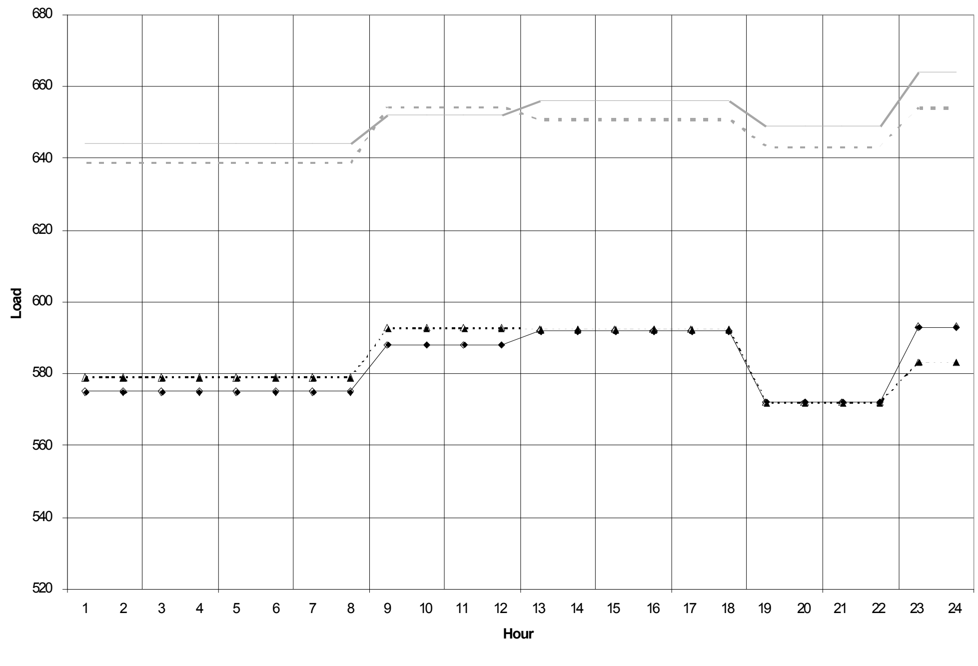


E19; SIC 4; Customer E_4_9;
Coefficients(Level, Daily, Share) : -1.17, -0.01, -0.7 (2002) 0.2, 0.66, 0.05 (2003)



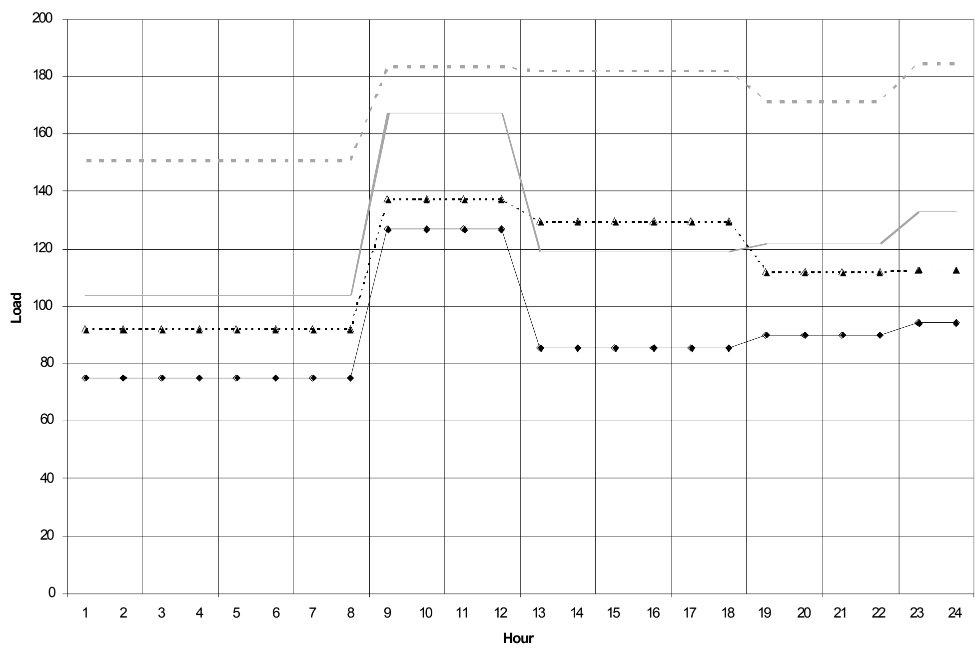
E19; SIC 4; Customer E_4_11;

Coefficients(Level, Daily, Share) : 0.01, -0.01, 0 (2002) 0.03, 0.04, 0 (2003)

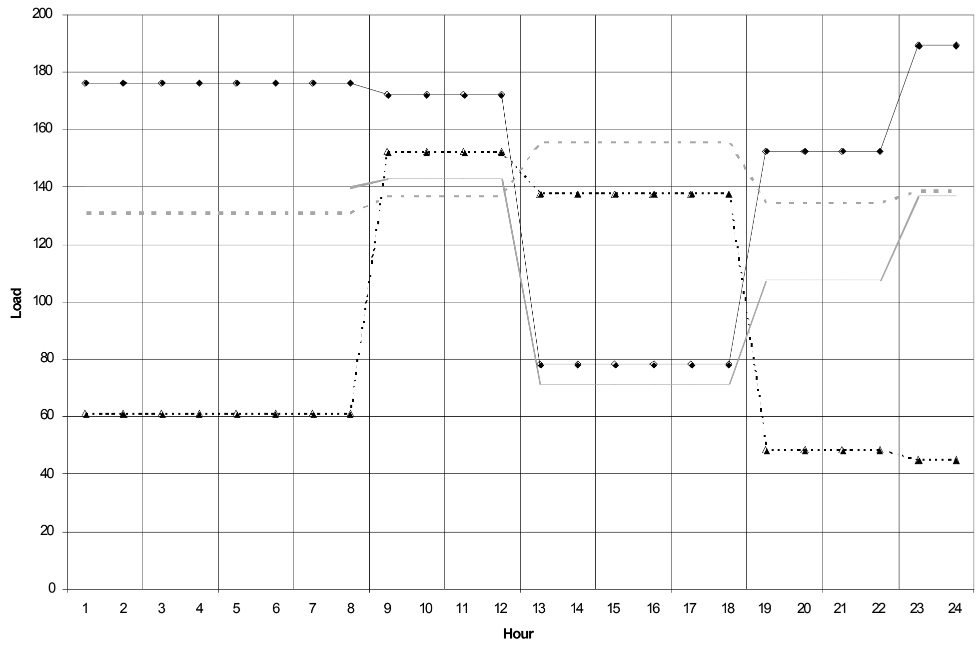


E19; SIC 4; Customer E_4_14;

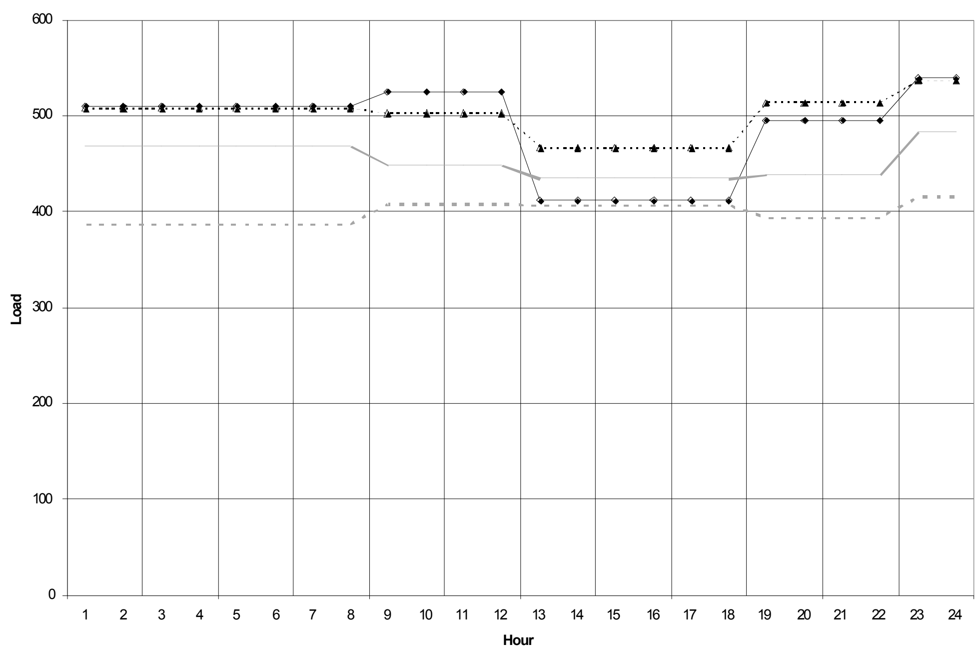
Coefficients(Level, Daily, Share) : -0.24, -0.13, -0.09 (2002) -0.54, -0.42, -0.13 (2003)



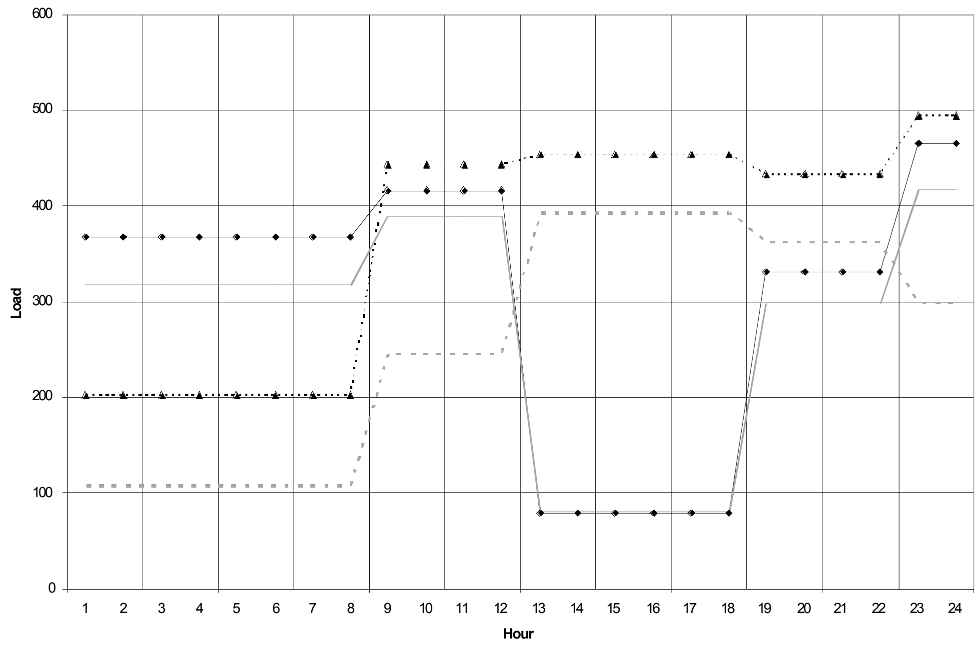
E19; SIC 4; Customer E_4_15;
Coefficients(Level, Daily, Share) : -1.65, 0.07, -0.67 (2002) -1.18, -0.24, -0.41 (2003)



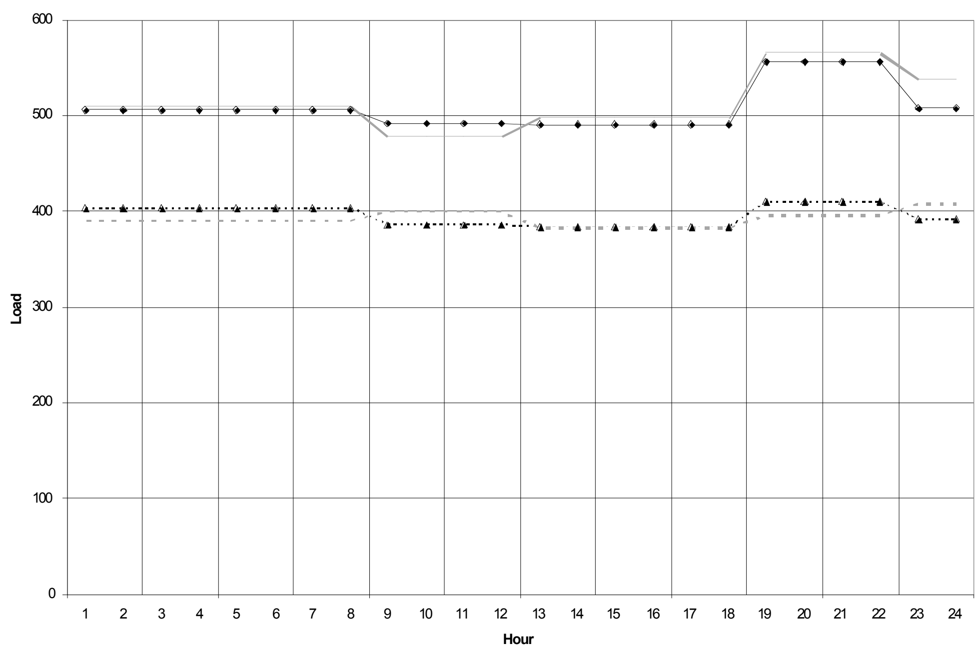
E19; SIC 4; Customer E_4_17;
Coefficients(Level, Daily, Share) : -0.08, 0.06, -0.19 (2002) 0.11, 0.13, -0.03 (2003)

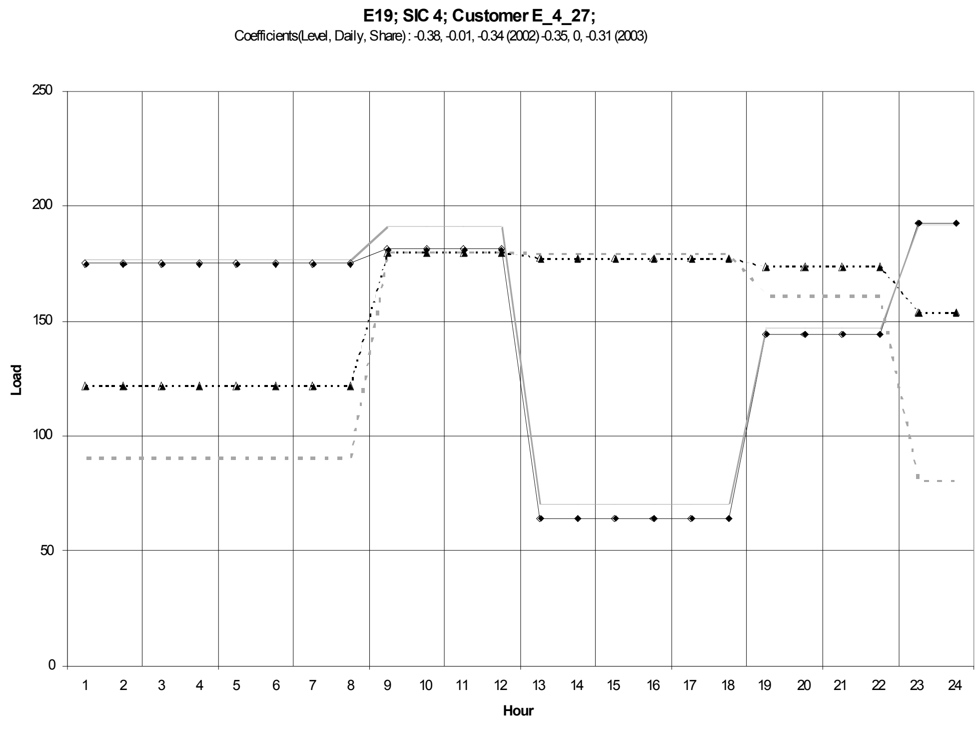


E19; SIC 4; Customer E_4_20;
Coefficients(Level, Daily, Share) : -0.79, -0.1, -0.72 (2002) 0.17, 0.35, -0.22 (2003)



E19; SIC 4; Customer E_4_21;
Coefficients(Level, Daily, Share) : 0.12, 0.18, -0.01 (2002) 0.14, 0.19, 0.01 (2003)




E19; SIC 4; Customer E_4_27;
Coefficients(Level, Daily, Share) : -0.38, -0.01, -0.34 (2002) -0.35, 0, -0.31 (2003)
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