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INDUSTRIAL RESPONSE TO SPOT ELECTRICITY PRICES: SOME EMPIRICAL EVIDENCE

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Abstract: Time of day prices for electricity are usually preferable to constant rates, as the true cost of generating energy varies over the course of a day. But time of day rates are still inefficient, because prices do not change in step with day by day random fluctuations in actual generating costs. Spot prices, which change every five minutes, can avoid this inefficiency by tracking actual marginal cost.

This paper empirically estimates the ability of industrial customers to respond to rapidly varying prices. The conclusion is that some customers will be able to react quickly to such prices. Because the estimates were made from a rate structure which is not a full spot pricing system, the magnitude of customer response remains problematic. Also, it appears that the utility in questions could make a minor change to its rate structure which would help both it and its customers.

INDUSTRIAL RESPONSE TO SPOT ELECTRICITY PRICES:

SOME EMPIRICAL EVIDENCE

I. Introduction

Electricity pricing schedules in which rates change periodically have become the subject of increasing discussion in the U.S. The proposal usually advanced is that different rates per kilowatt hour should be charged during different, prespecified, periods of the day, week, and year. Such rates are generally referred to as time of day rates, and have in fact been implemented in various parts of the U.S.[1/]

Time of day rates are superior to constant rates, as measured by overall welfare, because customers are more likely to pay the marginal cost of generating the electricity they use. When demand is high for a utility or reliability region, the marginal cost is high. Hence time of day rates are set higher for those periods when demand is usually high.

However, setting prices in advance can never achieve a full welfare optimum, since actual demand at any time in the future can vary considerably from its "normal" level. Furthermore, since prices are not adjusted in response to actual demands, the possibility arises that demand will be higher than available capacity, making rationing necessary.[2/]

A new concept for pricing electricity addresses these problems. New technology makes it possible to change prices every few minutes, and to signal the current price to customers. In this way, the price will track the <u>actual</u> marginal cost of generation, rather than the marginal cost of generating the amount of power "usually" demanded at that time of day. Furthermore the need for reserves, including spinning reserves, may be reduced if customers can respond rapidly enough to higher prices. When demand approaches the utilities capacity, it can respond by raising prices. Those customers most able to reduce demand will do so, returning the system to equilibrium. This concept, called "homeostatic control", was the subject of a recent conference.[3/]

An important issue in the value of such a pricing system is the customer's ability to respond to rapidly changing prices. For customers who are risk averse or who have to "lock in" their schedules in advance, it would be possible to sell options or futures.[4/] But it is still desirable to sell a substantial amount of power on a spot basis, to allow for unanticipated weather, outages, etc. (By charging a premium for options or futures over the expected spot price, the utility could make sure some customers would be willing to buy on the spot market.[5/]

How would customers react to spot prices? Presumably the best candidates would be large industrial customers, who already have automated process sequencing and control equipment and whose volume of electricity use would best justify the cost of special metering and communication equipment. But there are very few studies on how industrial customers react even to time of day rates, with their price schedules set a year or more in advance.[6/] There is apparently no data at all on how customers will react to spot prices.[7/] Until there is some evidence that customers can and will react within a few minutes to a newly announced price, the concept of really being able to maintain "homeostasis" in the utility system by spot pricing must be considered speculative.

This paper is a first attempt to explore this issue, using empirical data from a rate which has been in effect for two years in California. This rate schedule is not a true spot pricing system, but it has the essential feature: customers do not know how much they will pay for electricity until the time they actually use it. The reason is that the customers are assessed a charge based on their power demand at the time the entire system experienced its monthly peak. (So in fact, the customers don't know how much they paid for electricity until the end of the month! This complication can be put aside by assuming the customer calculates the probability that the current period will be assessed the special charge, and uses this probability to calculate the expected value of the current price.) Therefore it should give evidence about the ability of large customers to react quickly to newly "announced" prices.

Qualitative Discussion of Customer Ability to Respond to Spot Prices

It is rare for economists to concern themselves with fluctuations which take place from minute to minute.[8/] The next few paragraphs sketch the types of response we may expect on this time scale. The most important implication is that each customer will be unique.

It is important to distinguish among three different issues concerning the time a particular price lasts.

1. How long is each actual spot price in effect? For current time of day pricing schedules, for example, a price may be in effect from 5 p.m. to 10 p.m. each weekday. True spot prices might be posted for as little as five minutes.

2. How far in advance is the customer told what the price will be? For a time of day schedule which must be cleared by a regulatory commission, this will be months to years. For a spot price, the price may be announced only a few seconds ahead of time.[9/] Or the customer might buy an option which fixes the price several days in advance. Advance warning is important because it allows the customer to choose his capital stock, tell his workers what time to report for work, and set up an optimal production schedule in a job shop type of operation. (With advance warnings respectively of years, weeks, and days/hours.)

3. How far in advance are the <u>rules</u> which will subsequently generate the actual spot prices announced? Knowing these rules allows the customer to predict the probability distribution of spot prices, and plan accordingly. For example, he may redesign his plant to allow more short term adjustments to be made. Or he may sign contracts with his union to allow him to schedule breaks at a different time each day.[10/]

Suppose the customer is told there is a 50% chance that from 1 p.m. to 2 p.m. the next day, the price of his electricity will be $1.00/kwh. Otherwise it will be the normal 4¢/kwh. He then has three basic ways of reducing his electricity demand during that interval.

1. Rescheduling. He can take operations which he would perform anyway and which do not use much electricity, and move them to the 1-2 p.m. interval. Candidates are: lunch breaks, machine changeovers, and routine maintenance.

2. Storage. He can "store" electricity in advance, in one of two forms.
   a. As heat. He can run his air conditioners hard all morning, and be prepared to turn them off at 1 p.m. (This is particularly effective strategy for large buildings.)
   b. As embodied end product from an electricity intensive process. He can run the electricity intensive process hard all morning, and store its output to be fed to the next stage downstream. This type of adjustment requires advance provision in the form of surge tanks, and oversized capacity at critical stages of a product flow line.

3. Outright curtailment. He can simply shut down the power intensive unit at 1 p.m. If he has no room to store the upstream product, he may have to shut down the whole production line. In any case, he will have to shut down all of his downstream operations.

The costs of these three alternatives will depend on the particular plant configuration, labor costs, opportunity costs of reduced output, whether the plant is operating at full capacity, etc. It is clear that the costs and opportunities for curtailments in response to higher prices will depend on the particular circumstances of each plant. It is also clear that a plant designed for flexibility will have more opportunities for adjustment than will an automobile sytle assembly line. Thus the price elasticity of response to spot prices may improve for a decade or more after their introduction.

II. The San Diego Data

The actual rate structure used by San Diego Gas & Electric Company is very different than the spot market pricing system outlined above. It and the resulting data for estimation are discussed in this section.

All customers whose peak demand exceeds 4,500 kw during a month are placed on Schedule A-6. There are five charges on this schedule:

a. A metering charge of $600 per month.

b. A time of day differentiated rate, per kilowatt hour of electricity used. Presently usage during the peak hours is charged 1¢/kwh, usage during semi-peak costs .5¢/kwh, and usage during off-peak .25¢/kwh. These rates have changed every few months; they were about .3¢/kwh lower in early 1978.

c. An energy "adjustment" which is the bulk of the total expense. It is rougly 3¢ per kwh, regardless of time of day.

d. A peaking charge which depends on the amount of power used by the customer during the 15 minute period which turns out to be the time of the <u>system's</u> peak total load for that billing month. Thus neither the customer nor the utility know in advance which period will be the critical period.[11/] The charge is presently $7.67 per kilowatt. For a customer with flat demand over the course of the month, this charge could be 25% of his total bill.

e. Various minor taxes and special charges.

Only the fourth of these charges is of interest in this paper. This coincident peak demand charge (abbreviated Cpeak, to distinguish it from standard demand charges which are based on the customer's own peak demand during the month) can come to $250,000 per year, out of a total bill of $1 million. This rate structure has been in effect since late 1977.

<u>The Sample</u>

There are currently 21 customers on this rate schedule. For these customers, demand is recorded every 15 minutes by recording meters. In addition, six of these customers have special telephone hook-ups to San Diego Gas and Electric (SDG&E) which tells the customers the system's total load at each instant. Thus these customers can monitor the system load and assign a probability to the event "the next 15 minutes will show the highest system load for my entire billing month". When this probability is high, the expected value of the Cpeak charge is also high. Most of the time, however, this probability will be zero. The remaining customers, who lack the telephone hook-ups, can also estimate probabilities, but their estimates will be much more diffuse.[12/]

Of the six customers with telephone links, three are government owned and three are privately owned manufacturing plants. Six months of data were selected from each of the three industrial customers; June, July, and August 1978 and 1979. This provided about 120 observations on each customer.[13/]

Very important additional information was the actual daily SDG&E peak system load, in MW, and its time of occurence.[14/] This data was used to generate probabilities that each 15 minute interval would be the critical one.

Problems with the Data

The only major problem with this data is that the six customers who received the real time information by telephone were self-selected. Presumably they felt that the monetary value of this information was worth the cost of the leased phone line and the associated analog to digital conversion equipment. These six are not likely to be typical of the 21 customers on schedule A-6. They will have the highest marginal benefit from the improved probability estimates. (But not necessarily the highest total benefit from adjusting their demands to the Cpeak charge.)

Furthermore, San Diego is not a "typical" industrial city. It is impossible to say to what extent San Diego's largest electricity users response to this rate structure is typical of how others would respond. Therefore all of the estimates in this paper must be interpreted as conditional on the observed sample.

Other minor problems were encountered. Some customers' demand data was mildly multicollinear over the six month sampled. July 3 and other days adjacent to holidays were dropped when appropriate.[15/]

III. An Econometric Model of Demand as a Function of Spot Prices

Customers will respond to the random portion of San Diego Gas & Electric's price schedule in two stages. First, they will estimate the probability that the Cpeak charge will be assessed on their demand over the next few minutes. If it is assessed, then the cost of each kilowatt hour used over a 15 minute period is 4 x $7.67 or about $30/kwh. If it is not assessed, then the cost is about 4¢ per kwh. Customers may evaluate the probability of this Bernoulli distributed event using any of a wide range of current and historical information, by any means from subjective judgement to real time computer analysis.

Second, given their probability estimate, customers must decide how to react. Since these are large industrial customers, it is reasonable to assume that they are expected value maximizers. Therefore they will respond to the product of the probability (of incurring the Cpeak charge) times the charge. This gives them an estimated "pseudo price" for their electricity use over the next 15 minutes. The larger this pseudo price, the less electricity they will use. The amount of demand reduction depends on how much advance warning they get, and on how costly it is for them to cut demand quickly but briefly. It is this second response function (demand as a function of pseudo price) that we wish to estimate, since it will suggest whether the same customers would respond to true spot prices.

Estimating the Pseudo Price *

Before deciding whether to reduce its electricity use, each customer must estimate the pseudo price in the next few minutes. This is proportional to the probability that the next 15 minute interval will include the system's peak load for the month.

Utilities have developed for their own purposes load forecasting techniques which cover both of the relevant time scales (minutes and weeks). Time series and weather dependent methods have both been used. See for example the survey by F.D. Galiana [17/] and the multitude of papers published in the early 1970's, such as Galiana and Schweppe.[18/] These

*Casual readers may skip this subsection as the methods used are not crucial.

forecasting methods provide a "most likely" forecast for utility planning purposes, and often a (very conservative) confidence band of the maximum possible load. For calculating pseudo prices, such forecasts must be adapted to give the probability of an extreme value, rather than the most likely value.

For this investigation, a comparatively simple but adequate model was used to calculate pseudo prices. No weather data, weather forecast data, or knowledge of the minute by minute dynamics of system load was available.[19/] Therefore a purely time series model of daily peaks was developed, ignoring the minute by minute dynamics. Because of the pattern of SDG&E's peak loads, this model probably gives a good representation of the true pseudo prices.[20/] A completely accurate calculation would have to use Monte Carlo techniques, because of the very complex conditional relationships inherent in minute by minute data with high autocorrelations at the highest frequencies and at frequencies of days, weeks, and years. Furthermore, historical weather forecasts would be needed, since if tomorrow is likely to be hotter than today, today is unlikely to be a peak. (The real object here is to mimic the decision making procedures used by the customers. It is unlikely that all of them are this sophisticated.)

The basic probability calculating model is as follows.

$$(1) \qquad P[\hat{S}_n(t) = \hat{\hat{S}}] = P[\hat{S}_n(t) = \hat{S}_n] \times P[\hat{S}_n = \hat{\hat{S}} \mid \hat{S}_n = \hat{S}_n(t)]$$

where

$\hat{\hat{S}}$ = Highest system load for the billing month.

$\hat{S}_n$ = Highest system load for day n.

$S_n(t)$ = System load at time t of day n, where t is the midpoint of a 15 minute interval.

$\hat{S}_n(t) = \underset{-7 \le k \le 7}{\mathrm{Max}} [S_n(t+k)]$ = Highest level of system load during the current interval.[21/]

In words, the probability that the current 15 minute interval will turn out to have been the peak for the month is the probability that it is the peak for today, times the probability that the current reading will not be exceeded any other day this month.

One very important indentity dominates the evaluation of equation 1:

$$(2)\quad P[\hat{S}_n = \hat{\hat{S}} \mid \hat{S}_n = \hat{S}_n(t)] = \begin{cases} 0 \text{ if } \hat{S}_n < \hat{S}_k \quad \text{for any } k < n \text{ in the current billing month.} \\ P[\hat{S}_{n+1} < \hat{S}_n] \times P[\hat{S}_{n+2} < \hat{S}_n \mid \hat{S}_{n+1} < \hat{S}_n] \times \ldots . \\ \qquad \times\, P[\hat{S}_{20} < S_n \mid \hat{S}_{n+1}, \hat{S}_{n+2}, \ldots, \hat{S}_{19} < \hat{S}_n] \\ \qquad \text{if } \hat{S}_n > \hat{S}_k \text{ for all } k < n \text{ in current month.} \end{cases}$$

In words, day n is a candidate to be the peak for the month only if no previous day has had a higher daily peak. If day n passes this test, its chance of being a peak is the probability that all of the succeeding days of the month have lower daily peaks. (The exact form of equation 2 assumes 20 business days in a month.)

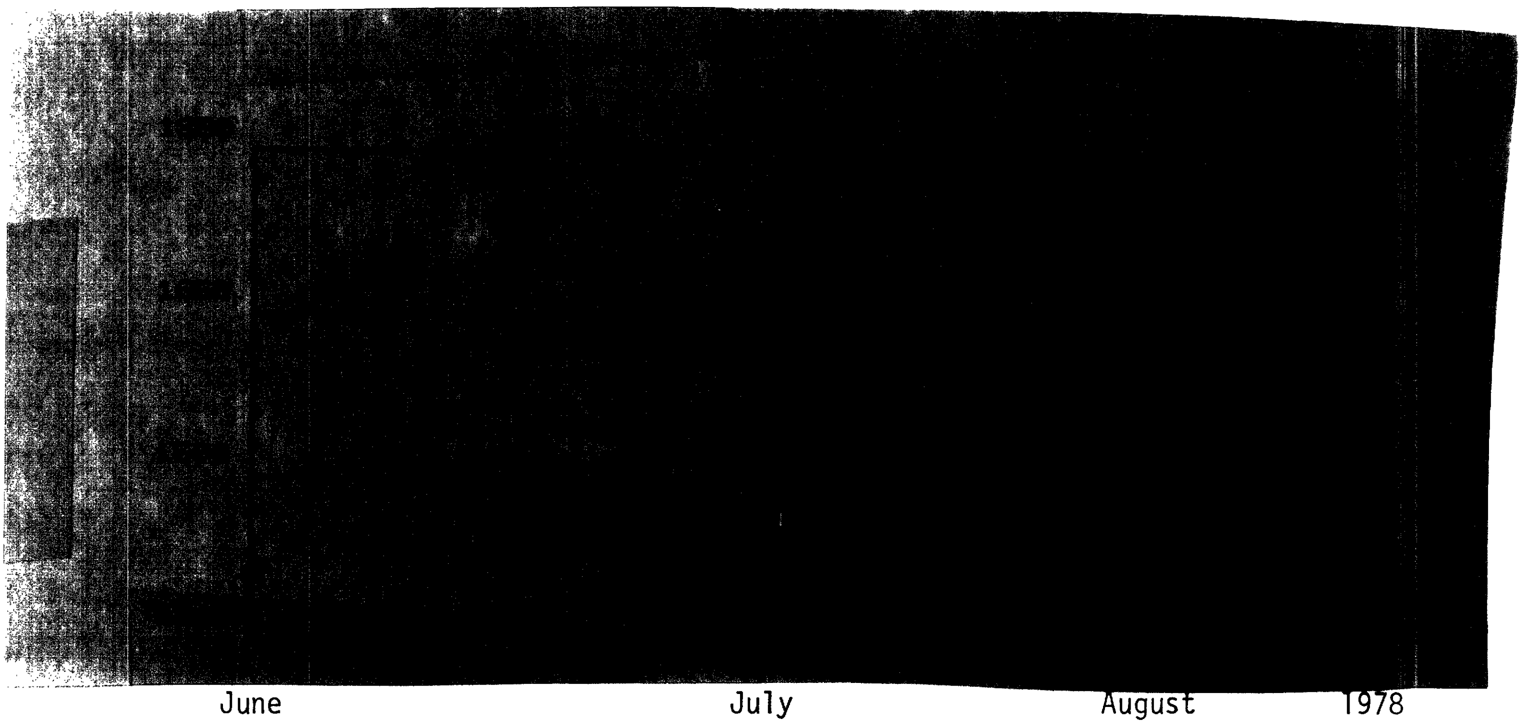
Finally, we assume that the daily peaks $\hat{S}_n$ are independent, identically distributed with a normal distribution. A constant variance but different mean is assumed for each of the six summer months in the sample.[22/] The normalcy assumption appears correct. But the independence assumption oversimplifies; there is autocorrelation between adjacent days, mainly due to weather persistence. The best way to correct for this would be with a weather dependent model, or barring that an autoregressive model.[23] Figure 1 shows the daily system peaks over the sample period, to illustrate the magnitude of the effects involved.

Equations 1 and 2 give the probability that the highest point in day n is also a peak for the month. There remains the issue of whether any particular time t is the highest for its day. Equation 1 was evaluated for only one time each day: that time period which, ex poste, was the peak for the day.

Examination of the daily load curves gives an indication of the magnitude of the first term of the right side of equation 1, evaluated at these particular times. Figure 2 shows the shape of Summer load curves. It is apparent that any of the intervals in early afternoon could turn out to be the peak for the day, depending on the vagaries of the minute by minute random walk refered to in footnote 21. In contrast, Figure 3 illustrates that Winter peaks are sharp and predictable. In fact,

FIGURE 1

DAILY PEAKS FOR SDG&E (MW)



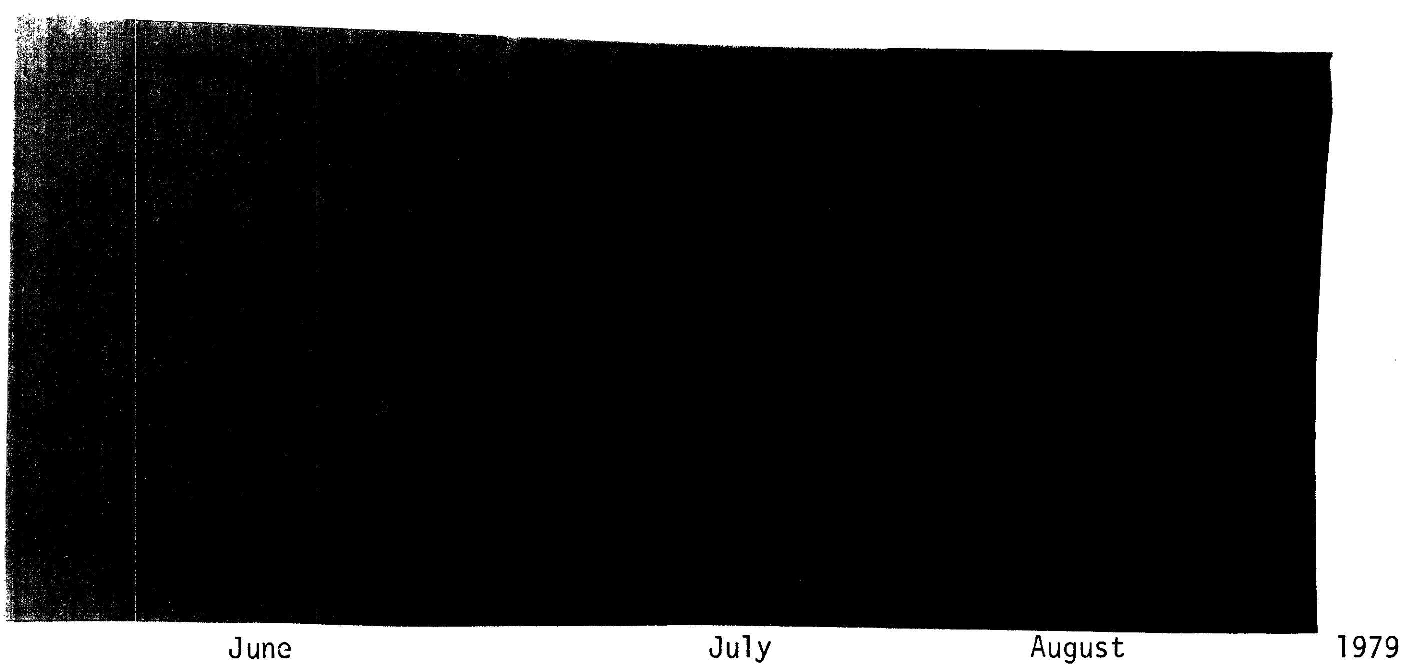


FIGURE 2

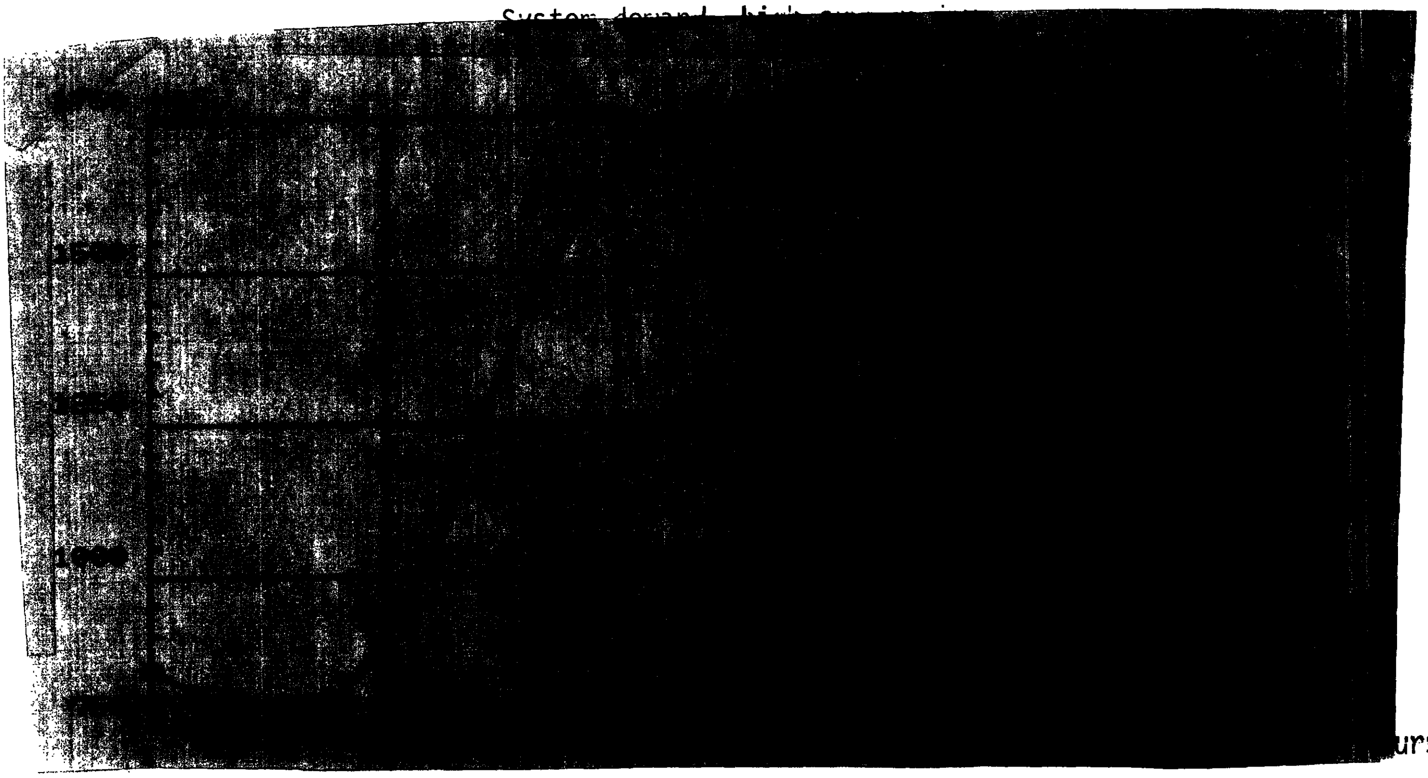
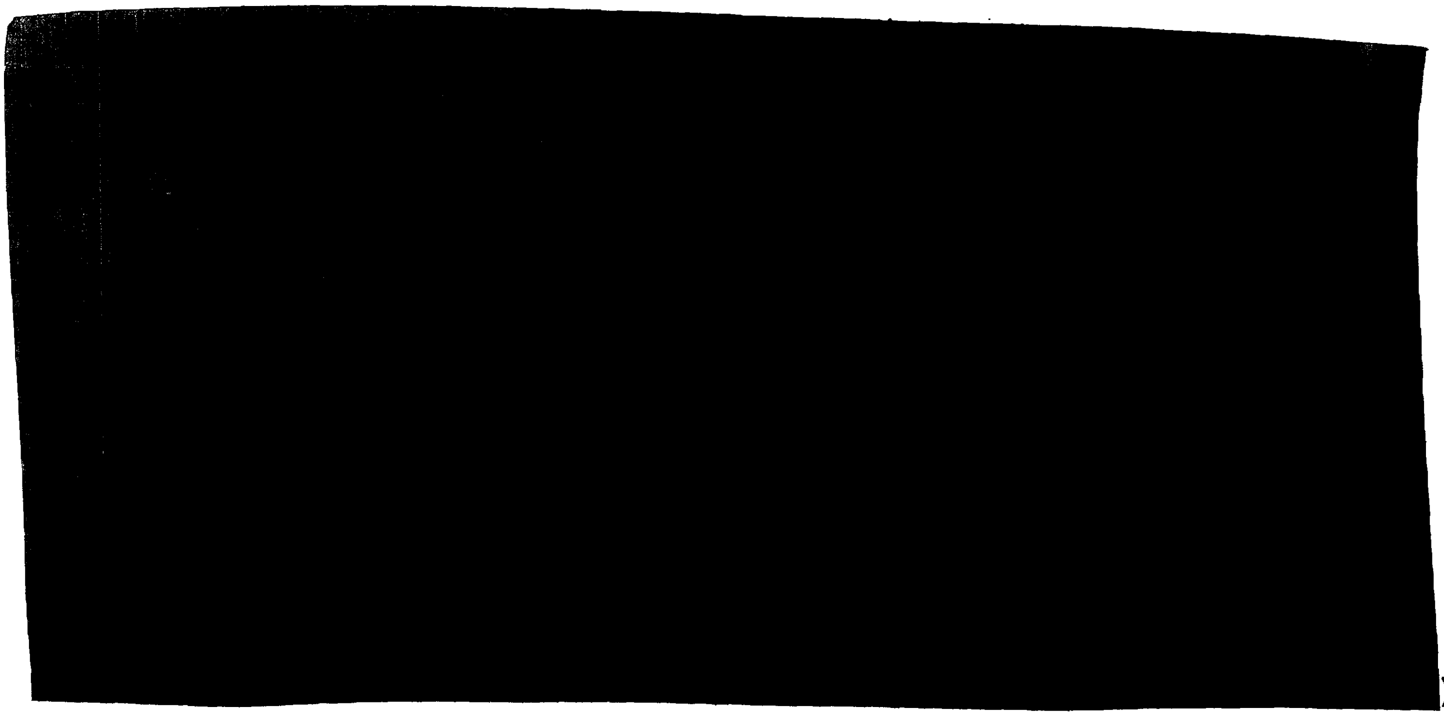


FIGURE 3



the peak during the Winter almost always occurs during the same interval as the previous day's peak. From this we estimate:

(3) $P[\hat{S}_n(t) = \hat{S}_n\ ]$ = Probability that the highest reading during the 15 minute interval around t is the peak for the day.

$$= K = \begin{cases} .25 \text{ in Summer months} \\ .8 \text{ in Winter months} \end{cases}$$

Note that the same estimate is used for each day in a sample.

The final form of equation 1 is therefore:

(4) P[The 15 minute interval around $\hat{t}_n$, the time of peak on day n, includes the monthly system peak]

$$\equiv P_n(\hat{t}_n) = K \times \begin{cases} 0 \text{ if } \hat{S}_n < \hat{S}_k \text{ , for any } k < n \\ \left\{\Phi[[S_n(\hat{t}_n) - \mu]/\sigma\ ]\right\}^{20-n} \end{cases} \qquad /24$$

where

μ = Mean daily system peak for the month

σ = Standard deviation of system peaks (about 100 MW)

20-n= Number of working days left in the billing month.

Φ = Unit Normal cumulative distribution function

Finally, adjusting for the fact that each kw demanded during the Cpeak interval incurs a charge of C, in dollars per kilowatt,

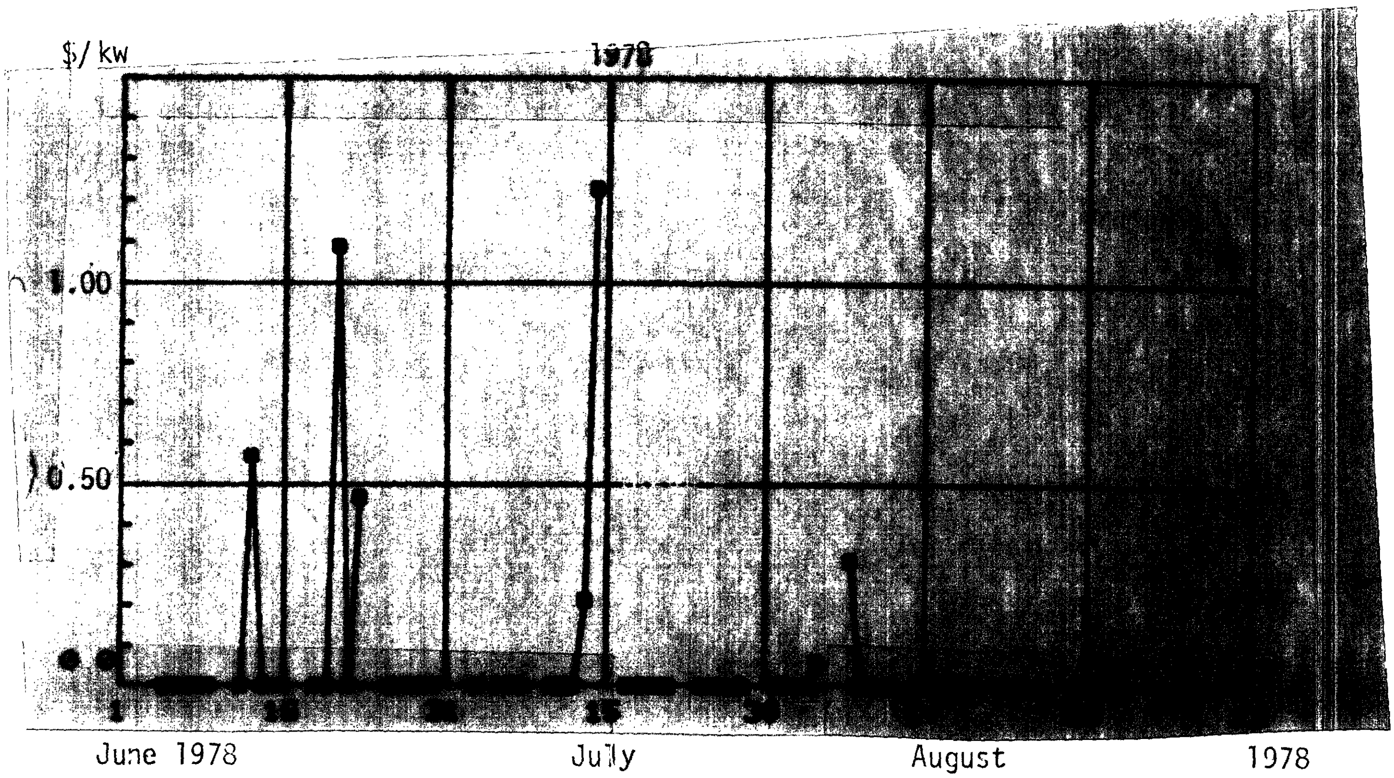
(5) $C_n = P_n\ (\hat{t}_n) \times C$

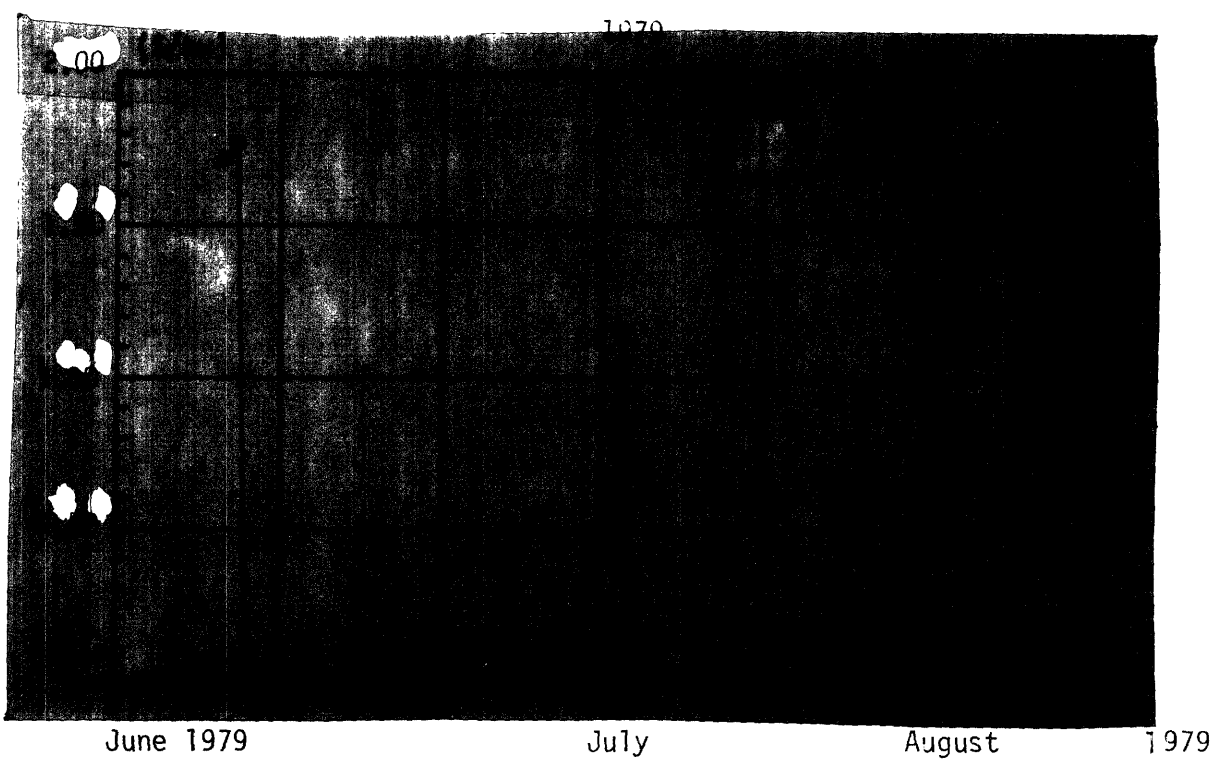
where C_n = pseudo price for day n at time t_n, in \$/kw.

Figure 4 shows the estimated pseudo prices over the course of the sample.

FIGURE 4

Estimated *pseudo prices*





Demand for Electricity as a Function of Spot Pseudo Prices

Given a continually changing pseudo price, which is not known in advance, how will a manufacturing customer respond? First, consider the demand for electricity during the periods when the pseudo price is zero. This will exhibit a normal pattern of diurnal, weekly, and random fluctuations, based on the hour by hour operations of the electricity using equipment in the plant. Then when the pseudo price rises above zero, the customer can respond by shutting down some equipment temporarily, turning up air conditioner thermostats, and similar measures discussed in section I. How much demand is cut back will depend on the cost of reduction compared with the amount saved.[25/] The marginal cost of reduction will be an increasing function of the amount of reduction, since the cheapest cutbacks will be made first.[26/] The costs will also depend on:

1. The amount of advance warning of high price. More advance warning will allow time for rescheduling. If the precise time of the peak can be anticipated, as is true in Winter months, then breaks, line changeovers, etc. can be scheduled in advance.

2. The time of day. Certain loads, which are only run at certain times of day, may be cheaper to curtail or reschedule than others. Also, if human intervention is required to reduce demand, operator attentiveness will be higher at some times than others, due to other demands on the operator.

3. Anticipated persistence of high prices. A pseudo price of $1/kwh which is expected to last for 30 minutes may elicit more response in each period than one which only lasts for 15 minutes. This will be the case if any cutbacks incur fixed costs as well as incremental costs per unit of time.[27/]

Curtailments, Δ, will therefore have the shape shown in Figure 5 as a function of pseudo price C and advance warning W, at some fixed time t.

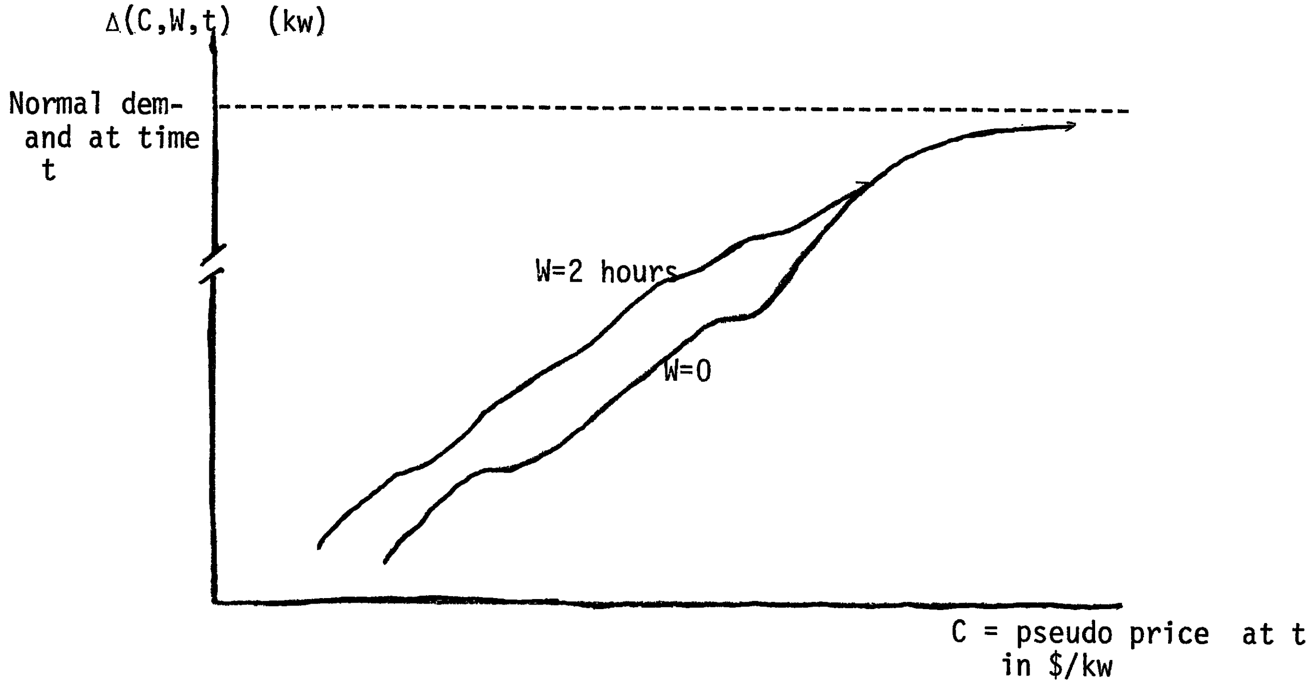


Figure 5
Curtailments as a function of price C
and advance warning W (illustrative)

Econometric specification of the curtailment response function

The basic econometric model estimated here uses lagged demand to provide a forecast of normal demands each day. Reductions below normal demand are then explained as curtailments due to spot prices.

Becasue of the time of day price structure of San Diego Gas &Electric rates, as well as the diurnal variations in the demand for electric services, demand will depend on time of day even if the spot pseudo price remains zero. One possible approach would be to attempt an engineering or econometric model of normal demand over time. This would be more complex than necessary to find the influence of spot prices.

Instead, current demand at the critical time $\hat{t}_n$ was regressed on demand of exactly one week before and on average demand for the same day. Thus normal annual, monthly, weekly, daily, and hourly demand variations (such as lunch hours) are removed. In addition any special features affecting an entire shift or entire day will be removed via the average daily demand term.

A linear version of Figure 5 was used to estimate the impact of spot prices. The final equation estimated was therefore of the form:

$$(6) \quad X_n(\hat{t}_n) = \alpha + \beta \bar{X}_n + \gamma X_{n-7}(\hat{t}_n) + \delta \bar{X}_{n-7} + \pi C_n + \theta S_n(\hat{t}_n)$$

where C_n = calculated pseudo price for day n, time $\hat{t}_n$

$\bar{X}_n$ = average demand on day n

$\hat{t}_n$ = the time of highest SDG&E system load on day n

n = index for day, month, and year.

$X_n(t)$ = demand for electricity at time t of day n.

$S_n(t)$ = System load at time t of day n. Used as an instrument for weather.

If customers can and do respond to spot prices, then π should be negative. The null hypothesis is that customers cannot respond quickly enough, in which case π will be zero. The last term, involving $S_n(\hat{t}_n)$ reflects the possibility that some customers have high air conditioning demand. During the summer the absolute level of system load in the afternoons will be correlated with the demand for air conditioning.

Equation 6 was estimated separately for each of the three customers. There is no rationale for thinking that the three have the same electricity using technologies, hence similar response functions $\Delta(C,W,t)$. Nor is there any reason to think they have the same pattern of shift changes, weekly and diurnal variations, etc., hence the same constants α,β,γ, or δ. Therefore separate estimates were made for each customer.[28/]

Various extensions of equation 6 may be appropriate.

1. The relationship between average demand for the day and demand at time t stays constant from week to week. Hence the constraint

$$(7) \quad \delta = -\beta\gamma$$

should hold.

2. The parameters of equation 6 may depend on the time of day. This will certainly be the case if the plant is in full operation during the day but reduced operation at night. Since the sample includes different times of day ranging from 10AM to 3 PM, there is possible aggregation error in the estimates. This could be easily corrected, albeit at some cost for computer time.[29/]

3. Equation 6 ignores the questions of warning time and anticipated persistence of high pseudo prices.

4. Finally, there is the question of short versus long run response. SDG&E's rate schedule has been in effect for two years. This is probably long enough to adjust plant operating procedures to the spot pricing system. But it is not enough to change the capital stock significantly. All else equal, we expect the π coefficient of responsiveness to increase in absolute value from year to year. In particular, customer 3 added the telephone hookup between 1978 and 79.

Robust Tests

Equation 6 assumes a very special response to the Cpeak charge. First, it assumes a comparatively sophisticated calculation of pseudo prices. An alternative, for example, would be to make a plant operator responsible for monitoring system load, and taking action when he deems it appropriate. Second, it assumed a linear response to the calculated pseudo prices. Given these assumptions, the test used to reject the null hypothesis (that customers don't respond) is then a one tailed test that the coefficient π is not zero.

More robust tests of the hypothesis that customers respond are also possible. A basic test is simply to compare demand on days with some chance of being a peak for the month against demand on days with no chance. This can be done in two ways. First, the demand at the same time of day can be compared for all days of the month. Second, equation 6 can be estimated with π restricted to zero. Then the residuals from this estimation can be summed over the days with a positive pseudo price and compared with zero. Either approach will, asymptotically, detect nonlinear responses and responses based on either more or less sophisticated calculations of pseudo prices.

All of the techniques discussed in this paper use some days of each month as controls for comparison with other days. There is one form of behavior which this will not detect under any circumstances. That is changes in behavior which do not depend on the actual system load on that particular day. For example, most peaks on Winter days occur during the interval from 5:45 PM to 6:00 PM. It might be cost effective to schedule shift changes for this period, regardless of the pseudo price on any particular day. In effect the customer would be substituting the average pseudo price for the actual spot price.[30/] The only way to detect such a shift is to compare behavior before and after the Cpeak charge was imposed.[31/]

IV. Results

The basic results are that two of the three industrial customers are clearly responding to the Cpeak demand charge during the Summers, while the third customer may or may not be responding. The magnitude of the response, however, implies that sudden adjustments of demand are quite costly. In one case a pseudo price of $.25 per kw leads to a demand reduction of only about 70 kw or 1.5%.[32/] For the second customer, the same price led to reductions of only about 50 kw, or 1%.

These results indicate that a significant amount of utility peak load reducing can be achieved by the Cpeak charge. At present the utility can impose a pseudo price of at most about $2 in Summer, and double that in Winter.[33/] This price would probably occur, for example, on the highest day of the year. Such a price would reduce demand of these two customers alone by 1 MW (compared with a maximum system load of about 2,000 MW).

The utility can get substantially more effect from this rate structure by moving toward true spot pricing, rather than the once a month but random Cpeak charge. A compromise would be to tie the charge to the <u>absolute</u> level of system load. In this way months where even the high for the month placed no strain on SDG&E capacity would cause little incentive for customers to shed loads. Conversely, the highest peaks of the year would encourage substantial conservation.

Even without such modifications, however, the coincident peak charge is clearly Pareto superior to the standard peak charge. Industrial customers can and do find it cost effective to lower their demands at the time of maximum system load.

Basic Results

The basic results for the three customers are shown in Table 1. The first four coefficients predict demand on days when pseudo prices are zero, and are not important. The important coefficient is π. It is negative for all three customers, but significant only for the first two. (At the 1% level in both cases.)

The final term in Table 1 is shown only for customer 3. For the other two customers the estimated value of θ was very small, insignificant, and its presence had almost no impact on the estimated value of π. Including

TABLE 1

Basic Results

$$X_n(\hat{t}_n) = \alpha + \beta \overline{X}_n + \gamma X_{n-7}(\hat{t}_n) + \delta \overline{X}_{n-7} + \pi C_n + \theta S_n(\hat{t}_n)$$

	Customer 1	Customer 2	Customer 3+
Constant, α	325 (336)	203 (70)	1076 (628)
Average demand for day, β	1.08 (.126)	1.08 (.109)	.88 (.14)
Lagged demand at same time of day, γ	.294 (.074)	.120 (.099)	.00 (.08)
Lagged average demand, δ	-.333 (.138)	-.248 (.140)	-.13 (.10)
Effect of pseudo price, π, in kw response per \$/kw pseudo price	-288* (60.4)	-194* (56.0)	-46.4+ (120)
Effect of absolute system load, θ	---	---	.77 (.34)
R^2	.666	.976	.36
Durbin-Watson	1.50	1.61	1.39
Standard error	202	189	335

*Significant at the 1% level.

+Customer 3 did not install equipment to monitor system load until 1979. This table shows results from pooled 1978 and 1979 data. See text.

Standard errors are shown in parentheses. No adjustment for autocorrelation was made in the results shown here.

Number of observations is about 120.

17 of these observations have positive values of C_n.

absolute system load in the explanatory variables also caused a multicollinearity problem for customer 2. Therefore this term is omitted in subsequent analysis.[34/]

Several other more general specifications were tested for all three customers.[35/] These included: a) enforcing the restriction of equation 7 on the coefficients of lagged demand; b) allowing π to change between 1978 and 1979; c) allowing all other coefficients to change between 1978 and 1979; and d) correcting for autocorrelation of residuals. With one exception, these specifications did not change the value of the critical π parameter by more than 10 kw/$/kw, not enough to affect any conclusions. For example, forcing the nonlinear restriction that $-\delta=\beta\gamma$ changed the values of β and γ greatly. But in no case did it alter π appreciably, nor did it change the standard error of the equation. Thus the conclusion that customers 1 and 2 did reduce their demand in response to high instantaneous pseudo prices appears robust. Customer 3 remained ambiguous.

The one specification which did affect the value of π was to allow it to change between 1978 and 1979. For customer 2, this made an appreciable difference, as shown in Table 2.

	Customer 1	Customer 2	Customer 3
π(joint 78/79)	-288 (60)	-194 (56)	-47 (120)
π_{78}	-312 (116)	-364 (104)	15 (200)
π_{79}	-284 (72)	-131 (64)	-70 (136)

Table 2: Changes in price responsiveness between years (kw per $/kw)

For customer 2, a Chow test indicates that price responsiveness probable did change between the two years. However, the customer became less responsive, rather than more responsive as we would expect due to long term adaptation. Customer 1 also changed in the wrong direction, although not significantly.

Customer 3 also changed, showing a much larger response in 1979. This is to be expected, since this customer installed a telephone link to monitor system load, between the two Summers. However even the 1979 coefficient is not large enough to unequivocally reject the null hypothesis of no response.[36/]

Estimating changes from 1978 to 1979 was frustrated by the small number of days in the sample with non-zero pseudo prices. This is shown on Figure 4. Extending the sample to cover more months in each year is the only solution.

Robust Test Results

As discussed, equation 6 assumes a linear response to the spot pseudo price. It also assumes a moderately sophisticated calculation of this price. One test was made which did not require such assumptions. Equation 6 was estimated with π held to zero, i.e. assuming that customers do not respond to pseudo prices at all. Then the residuals from this estimation were summed over those days for which C_n was positive, i.e. on which there was some chance of a peak. Under the null hypothesis, the sum of these residuals will have mean zero, and asymptotically be normally distributed. But if a positive chance of a peak leads to reduced demand, the sum of the residuals will be negative, regardless of the exact form of the response function.[37/] The results are shown in Table 3.

It is clear from the bottom row of this table that customers 1 and 2 were indeed reducing demand when there was a significant chance of incurring a Cpeak charge. On the other hand it appears that customer 3 was <u>not</u> responding, at least not effectively. The sum of its residuals on the appropriate days was only .04 standard deviations below that expected by pure chance. Segregating residuals into 1978 and 1979 observations gives a positive sum for 1979. Again, the small sample problem mentioned in footnote 36 frustrates analysis of customer 3.

TABLE 3

A Robust Test of Response

$$X_n(\hat{t}_n) = \alpha + \beta \bar{X}_n + \gamma X_{n-7}(\hat{t}_n) + \delta \bar{X}_{n-7} + \theta S_n(\hat{t}_n) + f(C_n) + u_n$$

Estimate with $f(C_n) \equiv 0$ (no response)

Then find $V = \sum_{\substack{n \text{ s.t.} \\ C_n \gg 0}} [u_n + f(C_n)]$.

If $f(C_n) \equiv 0$ is true, then $V \longrightarrow \text{Normal}(0, N\sigma_v^2)$

where N is the number of days with $C_n \gg 0$.+

	Customer 1	Customer 2	Customer 3
V	-2578	-2425	-60
$\sqrt{N}\ \sigma_v$	852	770	1320
$V/[\sqrt{N}\ \sigma_v]$	-3.2*	-3.2*	-.04

*Significant at the .005 level.

+ In small samples, even if the true residuals are iid Normal, V will have variance;

$$\sum_{i,j} \sum_{\substack{\text{s.t.} \\ C_i C_j \gg 0}} [I - X(X'X)^{-1} X']_{ij}$$

Sample size: N=15, total sample size = 120.

Interpretation and Significance of Results

The results of this paper demonstrate that some large industrial customers can and will respond to rapidly varying ("spot") prices of electricity. This overcomes an important theoretical objection which has been raised to spot or homeostatic pricing, namely that customers could not respond rapidly enough to the price signals. But the results also suggest that the strength of the response may be low for some customers. On site interviews, and engineering/economic analysis in the style of Manichaikul and Schweppe[39/] would be needed to find out why customer 3 did not respond more. (Absent a much larger cross section than will ever come out of the current San Diego rate structure.)

How large is the response of the two customers who definitely did react? Measured conventionally, it is miniscule, especially if considered in terms of energy (kwh used during the 15 minute period) instead of power (kilowatts). Both customers showed an elasticity of roughly .002 in terms of power, one quarter that in terms of energy used over 15 minutes.[40/]

As mentioned earlier, even this small elasticity can be quite useful and cost effective for a utility which a) can use very high prices for short periods of time, and b) has the sole objective of delaying additions to capacity. The days of annual and seasonal peaks are guaranteed to have high pseudo prices. With high pseudo prices, the utility can cut several megawatts off its peak, judging by the results of the calculations in this paper.

It is also clear that, from the broader perspective of homeostatic pricing, the bang/bang feature of the Cpeak charge has undesirable properties. The pseudo prices will not correspond to true marginal generating costs for more than a few hours a month, since as long as an earlier day of the month had a higher system load, customers will have no incentive to reduce use, no matter how overloaded the SDG&E system is. In addition, the present pricing schedule presents problems to customers. First, it may not be cost effective for them to arrange load shedding procedures and equipment which will only be used a few hours a month, at most. Second, to truly minimize their expected electricity bill, they must continually calculate the probability that the next 15 minutes will contain the peak for the month. This requires an on line, real time computer, or a very alert human operator. SDG&E, on the other hand, can calculate these probabilities fairly easily, and do so for all affected customers at once. If the utility were to substitute either the probability, or better yet a true and guaranteed price in cents per kilowatt hour, for the load information now sent out on its telephone line, customers would not have to do these calculations. Thus there is a natural progression from the Cpeak charge to homeostatic/spot pricing. (Of course equitable distribution of the resulting savings to both customers and the utility might have to be negotiated.)

What would be the behavior of customers who faced continually evolving spot prices, rather than the bang/bang feature of the current price system? Unfortunately their response in the present case tells us only a little about the more general case. Most important, some of the customers would respond. (Remember the self selection bias in the current sample.) But it might become cost effective for them to undertake a much broader adaptation to the new rate structure. At present, only a few relatively unimportant pieces of equipment may be set up to drop loads at critical times. Equipment for which there is a high cost for the shutdown/startup sequence would not be set to respond. But in a situation with homeostatic prices, there would be longer periods of high prices. (It is also likely that prices early in the day would give better indications of prices later in the day. With more advance warning, responses would also be higher.) Hence more response would probably occur under homeostatic pricing than is suggested by the very low elasticities calculated here.[41/]

Possible Biases and Errors

Many real or potential problems with this study have already been mentioned. This section attempts to list all which may be important. In many cases, the data to ameliorate them is already available, and merely needs to be mounted on a computer.

1. Limited sample. Because of time and data availability, the sample estimated was limited to one observation per day, for six months (out of two years) and 6 customers (out of 21 on this rate schedule, of whom six receive real time telephone signals). A larger sample would provide more information.

2. Advance warning. There is theoretical reason to expect more response with several hours of advance warning that a system peak might be approaching. This was not tested.

3. Time of day. If shift changes, breaks, or other changes in production occur between 12:30 PM and 2:30 PM, then responsiveness to pseudo price may depend on time of day. Also, when a high system load occurs late in the afternoon, there is less chance that it will be followed by an even higher reading. Therefore the "constant" κ in equation 4 may depend on the time of day.

4. Biases in the calculation of the pseudo prices, C_n. Most days unequivocally had a pseudo price of zero, throughout the day. The exact price on other days is harder to calculate. But the ordinal ranking of days would probably not change much when using more sophisticated calculations.

5. Autocorrelation. The Durbin Watson statistics from the estimates of equation 6 consistently indicated positive autocorrelation in the residuals. This is to be expected. The regressions used demand lagged by one week; demand the previous day would be positively correlated. Also, because weather persistence was not considered in the calculation of pseudo prices, these prices tended to be autocorrelated. Equation 6 was estimated with a correction for first order autocorrelation. But the maximum likelihood values of ρ were only about .1 to .15, and this adjustment had little impact on the estimates.

7. Omitted variables. Temperature or some other measure of air conditioning load might be important for some customers. Using gross system load as an instrument is acceptable, but not efficient since it contains many other

components also.

A more complete model, which would better predict demand at each time in the absence of a Cpeak charge, would have given smaller residuals and hence tighter estimates of responsiveness to the Cpeak charge. Such a model might improve the low R^2 of equation 6 for customers 1 and 3.

8. Evolution of customer behavior over time. Tests for changes from 1978 to 1979 were tried, but were inconclusive. Putting in 12 months of data for each year would allow tests with higher power.

Conclusion

San Diego Gas and Electric Company has put into effect a rate schedule in which the cost per kilowatt hour is not known in advance. Several of its largest customers have chosen to pay the fixed costs for telephone equipment which allows them to better monitor the price at each moment. These customers then adjust their demands for electricity according to the instantaneous or "spot" price.

The success of this concept, at least on a limited scale, suggests the value of further pursuit of the more general concept of "homeostatic pricing", in which the price of electricity changes continuously, reflecting the true marginal costs of generation at that time. In fact relatively slight changes in the rate structure in the direction of homeostatic pricing may be the logical next step.

FOOTNOTES

1. For examples, see John T. Wenders and Lester D. Taylor, 1976, "Experiments in seasonal-time-of-day pricing of electricity to residential users," The Bell Journal of Economics, volume 7 pp 531-552.

2. Roger Sherman and Michael Visscher, 1978, "Second best pricing with stochastic demand", American Economic Review, volume 68 no. 1, pp41-53.

3. MIT Center for Energy Policy Research, and Electric Power Systems Engineering Laboratory, "New Electric Utility Management and Control Systems", conference proceedings, June 1979. See also the forthcoming paper, Fred C. Schweppe et al, "Homeostatic utility control", IEEE Transactions on Power Apparatus and Systems.

4. For example, the option to purchase a fixed amount of electricity at a prespecified price, from 10AM to noon the next day. Such options could be "sold" electronically the night before.

5. Regulatory intervention in the price setting process would presumably be necessary. William Vickrey, "Efficient pricing under regulations: the case of responsive pricing as a substitute for interruptible power contracts," June 1978, unpublished, proposes a "pool" which would be rebated to customers at the end of the year. His concept of "responsive pricing" is very similar to "homeostatic" or "spot" pricing.

6. But see B.M. Mitchell, W.G. Manning Jr., and J.P. Acton, "Electricity Pricing and Load Management: Foreign Experience and California Opportunities," Rand Corporation Report R-2106-CERCDC, March 1977.

7. Although the British apparently use a related system called "Peak Period Warnings." Ibid.

8. An exception is M. Barry Goldman and Howard B. Sosin, 1979, "Information dissemination, market efficiency, and the frequency of transactions," Journal of Financial Economics, Volume 7 no. 1, pp 29-61. The analogy between a stock market and the electricity "market" implied in this paper is strong.

9. But each customer could generate a subjective probability distribution of the price at some future time. As the time approaches, the distribution would usually become more peaked. Note the value of a futures market for electricity as a means of "pooling" different customers estimates of the spot price at a later time.

10. For the San Diego Gas &Electric rate structure discussed in this paper, the answers are: a rate is in effect for 15 minutes; the customer is told the rate in the middle of the period to which it applies, so there is almost no advance warning; the rules were approved by the CPUC more than two years ago.

11. However only peak period hours are eligible. During Winter months, the peak must fall between 5 PM and 9 PM, PST. During the Summer months, the peak must fall between 10 AM and 5 PM, PST. Weekends and holidays are ineligible. Thus the customer does not have to monitor the system load at other times.

12. The peak during the Summer is heavily influenced by air conditioning load. Therefore these customers would use a temperature related estimate of probabilities.

13. One customer installed the telephone monitoring equipment midway through the sample.

14. This data had holes which were filled by interpolation from hourly load profiles.

15. Average demand for the day was used as the criterion for dropping a day.

16. No footnote.

17. F.D. Galiana, "Short term load forecasting," 1976 (?), IEEE Transactions on Power Apparatus and Systems (?).

18. F.D. Galiana and F.C. Schweppe, 1972, "A weather dependent probabilistic model for short term load forecasting," paper C 72 171-2, IEEE Winter Meeting, 1972.

19. Such information would be available to customers, with some effort. Therefore customers could have better estimates of pseudo prices than the estimates developed here. This will introduce some measurement error into the regressions, as discussed below.

20. It is reasonable to treat each customer as a perfect competitor, since each customer's load is less than .5% of the system peak load.

21. Movements over this short a time period can probably be described as a Wiener process, ignoring drift. Note that the volatility of this process may be important. If one waits until the middle of a 15 minute interval to realise one should reduce demand, the effect will be proportionally reduced. (The 15 minute demand meters integrate over each quarter hour.)

22. To allow for seasonal variation and trends in peak loads.

23. First order autocorrelation of daily peaks was about .7. However even an AR(1) model would not eliminate measurement error, since most of this persistence was due to weather.

24. Actually, if $\hat{S}_k - \hat{S}_n < 10$ MW this was adjusted to allow for the possibility that demand would rise several MW during the next few minutes. Ex poste, we know this didn't happen. But that could not have been known at the time.

25. Actually the expected value of savings, since pseudo price is an expected value. We assume all customers are risk neutral for such small dollar amounts.

26. Except that there may be an initial nonconvexity, if there is a fixed cost which must be incurred before the first curtailment can take effect.

27. See Mohan Munasinghe and Mark Gellerson, "Economic criteria for optimizing power system reliability levels," 1979, The Bell Journal of Economics, Vol. 10 no. 1, pp 353-365 for a discussion of the cost to customers of blackouts. Such costs are an upper bound on the amount of price incentive needed to achieve voluntary demand reductions.

28. Because of the approximate methods used to estimate the pseudo prices, there will be measurement errors which should be correlated between customers. Therefore the residuals should be positively correlated on days when C_n was positive. In fact, the residuals were slightly negatively correlated, perhaps because of time of day effects. Therefore Zellner estimation was not attempted.

29. Such estimation would have been simple if the data were available on computer tape, since there would then be massive amounts of information available to estimate normal demand at each time of day. Instead, the 15 minute demands were available only on paper.

30. If half of all Winter peaks fall during this interval, the average pseudo price is about 70¢ per kilowatt hour, over the entire month!

31. See Electrical World, September 15, 1979 pp 138-139 for a comparison of average demands of pooled schedule A-6 customers at the time of peak, before and after the rate was changed.

32. Some results have been scaled to protect the confidentiality of customers.

33. Since the peaks are sharper in Winter, the customer can be more certain which 15 minute interval will contain the peak.

34. These two customers may still have had air conditioning loads. The daily average demand, $\bar{X}_n$, would also pick up air conditioning demand.

35. Given an unlimited amount of data with no multicollinearity problems, it would be ideal to use the most general specification in all tests. As shown, this would not have changed the conclusions.

36. The power of the test on 1979 data alone is low. There are only 8 days with positive pseudo prices in Summer 1979. Four of these are consecutive days in August. (See Figure 4.) Customer 3 happened to have very high demand on 3 of these 4 days, perhaps because of something happening that week.

37. The null hypothesis is thus that $f(C_n) \equiv 0$, compared with $f(C) < 0$ when $C > 0$. In either case we expect that $f(0)=0$. We also know that $f(C)$ is non increasing, but this restriction is not incorporated into the test.

38. No footnote.

39. Y. Manichaikul and F.C. Schweppe,"Physical/ economic analysis of industrial demand," presented at the IEEE Power Engineering Society 1979 Summer Meeting, July 1979.

40. Since the impact of a $7/kw Cpeak charge, measured on demand over 15 minutes, is $28/kwh. Of course if the peak were measured instantaneously, this would be an infinite chargeper kwh at the critical instant!

41. Of course this depends on how the homeostatic prices compare with the Cpeak charge. Consider a Cpeak charge of $1 per kw, in effect for 15 minutes. Compare this with a spot charge of $1 per kwh, in effect for an hour. Both raise $1 of revenue from a 1kw load which is on forthe entire hour. But the customer might be willing to turn off his equipment only for the former rate, for only 15 minutes. On the other hand the true higher costs to SDG&E are probably incurred over several hours. In addition the spot price would be more predictable, allowing customers to take actions which require longer lead times.