Improving Electricity Peak Demand Forecasts with Measured Data: An Application of PG&E's Residential End-Use Metered Data

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Forecasting in an era of integrated resource planning requires end-use detail, not only for annual energy, but also for hourly loads. While peak and hourly end-use demand forecasting models have been available for some time, measured data to support these activities have been scarce. In late 1984, Pacific Gas and Electric Company began metering domestic appliances for over 700 residential customers. In this paper, we analyze central air conditioner data collected in this project between 1985 and 1989 to develop inputs for an electricity peak demand forecasting model currently in use in California.

We describe the structure of the forecasting model, and discuss the requirements the model places on data development. We examine the issues associated with aggregation over days and over geographic regions.

Introduction

Examination of hourly end-use load shape data can improve understanding of factors influencing demand. This improved understanding can be used in assessing the cost-effectiveness of alternative resource options. In the future it may also be possible to aggregate end-use load shapes to make annual demand forecasts. Until recently, however, little metered end-use data were available, and the end-use load shape inputs to forecasting models were often based solely on engineering judgment. Information from recent end-use data collection projects can be used to verify and improve existing estimation techniques (Eto et al. 1990).

Among the end-use load shape data collection projects is the Appliance Metering Project (AMP) conducted by Pacific Gas & Electric (PG&E), for which metered data was collected from over 700 residential customers beginning in 1985. In this paper, we report results of our analyses of the central air conditioner load data collected in this project between 1985 and 1989. These analyses centered on the development of new inputs to the peak residential demand forecasting model currently used by the California Energy Commission (CEC) in their biennial forecasts of electricity demand. We examine various options for aggregating the data to produce these inputs and discuss trade-offs between precision and accuracy that the aggregations may involve.

Data

Load Data

PG&E's Appliance Metering Project is the first large-scale end-use metering project in California (PG&E 1987). Starting in late 1984, over 700 single-family owner-occupied residences have been continuously metered. In designing the project, PG&E was particularly interested in improving its understanding of the contribution of space cooling energy use to system loads. As a result, the geographic distribution of metered households is concentrated in the hot central valley of California, where the demand for cooling is greatest. For each household, total household load and two other end uses were metered. The air conditioning end use included data from 415 central air conditioners. Only analyses for central air conditioning data are included in this report. (Analyses for other end uses are discussed in Eto and Moezzi 1992.)

Only single-family residences were metered. Although PG&E developed analysis weights to make the sample more representative of the total residential class, results presented in this report were developed through unweighted analyses of the data. Thus our analyses are reflective only of loads for single-family residences. Furthermore, for these loads, we have not assessed what biases that may exist as a result of the process used to select participants for the project.

Weather Data

For our analyses, cooling load data were aggregated according to metered residence location into climate regions used by the CEC to forecast loads for the PG&E service territory. Each CEC climate region was associated with a NOAA weather station reporting weather data on an hourly basis. The Sacramento NOAA station is used for CEC Region 2, the Fresno NOAA station for Region 3, and the San Jose NOAA station for Region 4. Weather at the Fresno NOAA station is very hot, at the Sacramento station hot, and at the San Jose weather station relatively mild. For our analyses we used dry-bulb and wet-bulb temperature.

Approach

Forecasting Model Structure

CEC uses a peak demand model that was developed in-house in the late 1970s (Jaske and Paige 1979). The CEC model was designed in conjunction with the end-use annual energy forecasting models. For the residential sector, the CEC model requires annual energy forecasts for 5 space-conditioning end-uses for each distinct geographic region considered, and for 14 non-space conditioning end-uses for the PG&E service territory as a whole. We describe only the aspects of the model pertinent to the cooling end-use.

The CEC model is in principle capable of producing forecasts for days which are not peak demand days. Historically, however, the focus of applications of the CEC model has been to produce system peak day load forecasts. To the extent that average day and peak day demand are different, different modeling approaches for average day and peak day forecasts may be required. We examine the suitability of using the model to predict load shapes on average as well as peak days.

For the cooling end use, the CEC model allocates forecasts of annual cooling energy use to hours of the year in two steps, using information on weather conditions measured at the NOAA weather associated with the region (CEC 1991). First, annual energy is allocated to daily energy according to a three-day weighted average of a weather parameter called the temperature-humidity index (THI). The temperature-humidity index is a function of dry-bulb and wet-bulb temperature, designed to reflect human comfort. By assumption, only values of THI greater than 68 contribute to cooling loads. This contribution is expressed as THI degree-days (THI-DD), a daily measure defined as the sum of all positive values of the difference between hourly THI and 68. A weighted average of daily THI-DD (WTHI-DD) is computed from THI-DD on the forecast day and on the two preceding days. For each station, the long-term annual average sum of daily THI-DD (ATHI-DD) is also computed. Annual energy is allocated to the peak day by scaling the forecasted annual energy by the ratio of peak day WTHI-DD to ATHI-DD.

In the second step the model distributes the daily energy estimates for cooling end use to hours of the day according to a load shape derived from regional weather data and a two-dimensional array called a time-temperature matrix. The time-temperature matrix defines a correspondence between a cell, defined by a combination of hour of day and temperature-humidity index, and an average load in kWh for a particular end-use (here central air conditioning). The matrix is used to generate a day's load shape based on 24 hourly values of THI, with each hourly value a predicted load in energy units. The resulting load shape can be normalized (as it is for the purposes of the CEC model) by first summing the 24 predicted hourly loads and then dividing each hourly load by that sum, such that the 24 rescaled hours add up to one. The normalized load shape is subsequently scaled according to the THI-DD based allocation procedure described above.

To produce peak day forecasts for space conditioning end uses, CEC Staff use weather data associated with historical system peaks. For their 1991 forecasts, CEC used weather data producing the median value for conditioning loads coincident with total system peak among annual system peak day weather conditions from 1976-1990 (CEC 1991).

Developing a Time-Temperature Matrix

In this section we describe the general construction of a time-temperature matrix suitable for use in the CEC residential peak model, using as an example a time-temperature matrix constructed by combining data from all regions and from all five years of AMP central air conditioner data. In later sections, we examine various disaggregations of the data, including the development of region-specific matrices.

Figure 1 shows the resulting raw time-temperature matrix. Each cell represents a cell mean for an observed hour-THI combination. This mean load is computed from all hours assigned to the cell, over residences and dates. The data do not fill every cell, and exhibit unevenness across adjacent values when plotted, particularly at time-temperature combinations with the highest loads and accordingly little data. Intuition suggests that

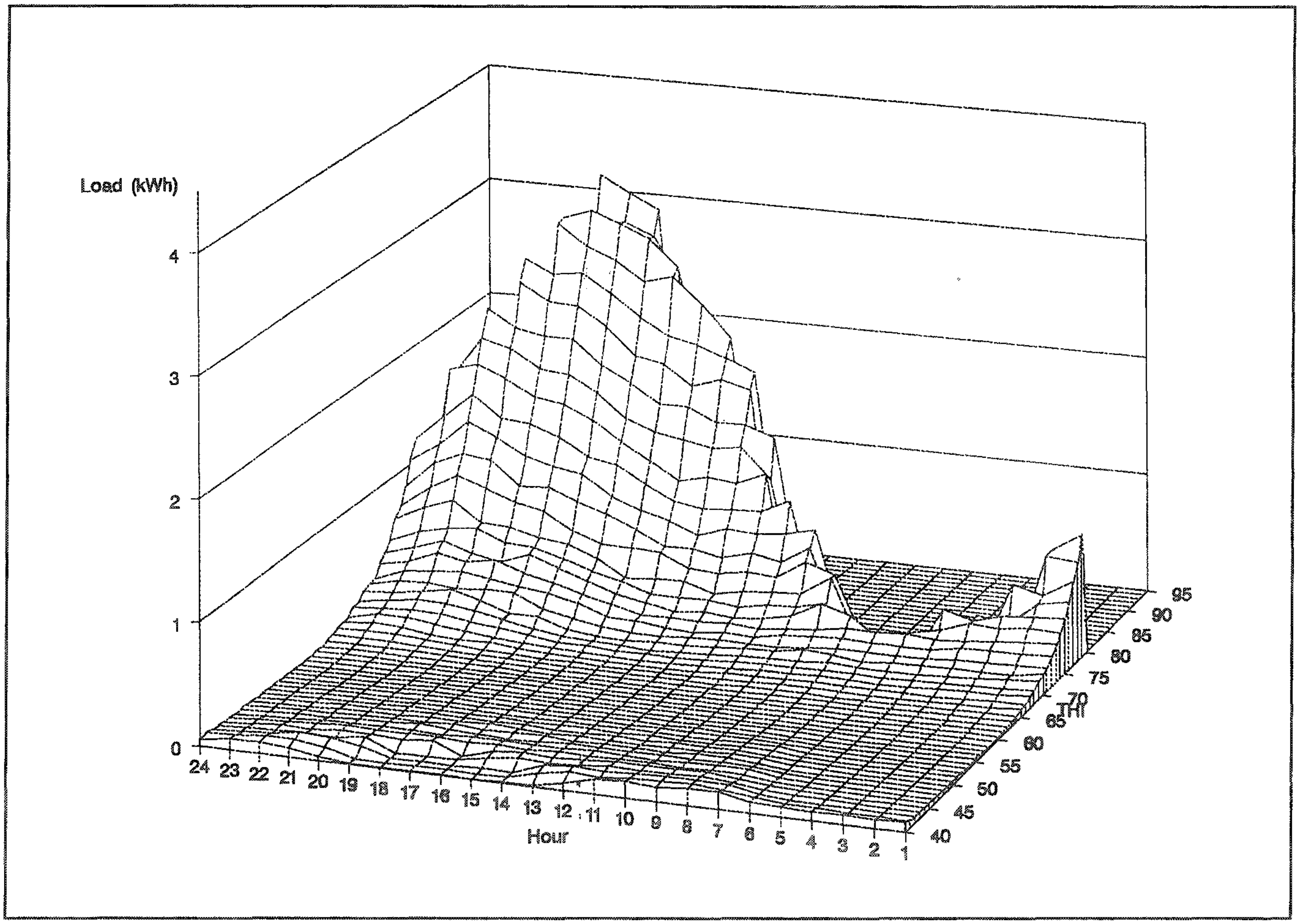

Figure 1. Raw Time-Temperature Matrix for Central Air Conditioning

time-temperature matrices ought to behave smoothly across the time-temperature load surface. Under this assumption, an appropriate smoothing algorithm can theoretically improve the estimates of mean cell load (and possibly be used to extrapolate from the observed data for small changes in THI). This approach is particularly appealing if certain cells contain few observations.

Instead of using the raw time-temperature matrix itself for the CEC model, we used a smoothed version of the matrix. To smooth the surface of the matrix, we modeled average central air conditioner demand for a given hour as a function of a maximum demand level weighted by a two-parameter Weibull probability distribution on THI, with the two parameters of the Weibull distribution having an explicit dependence on hour of the day. Details are discussed in Ruderman et al. (1989). Figure 2 shows the smoothed time-temperature matrix[1].

Method of Evaluation

We compared our backcasts to the average load shape of the sample on the day on which the historic weather was taken[2]. Thus, for each CEC Region we derive a pair of load shapes for each day 1985-1989. Each pair consists of a backcast load shape derived from applying hourly THI values for the CEC Region's NOAA weather station to the time-temperature matrix, and a sample mean load shape derived from all metered central air conditioner data for that region and day.

In comparing load shapes, we relied on both visual inspection and more formal, quantitative, measures of fit. For each day's pair of load shapes we computed (1) the difference in hours between the peak hour of the sample load shape and the peak hour of the backcast load shape, (2) the difference between level of peak hour of the sample load shape and level of peak hour of the backcast load shape, (3) the difference between sample 4 p.m. load

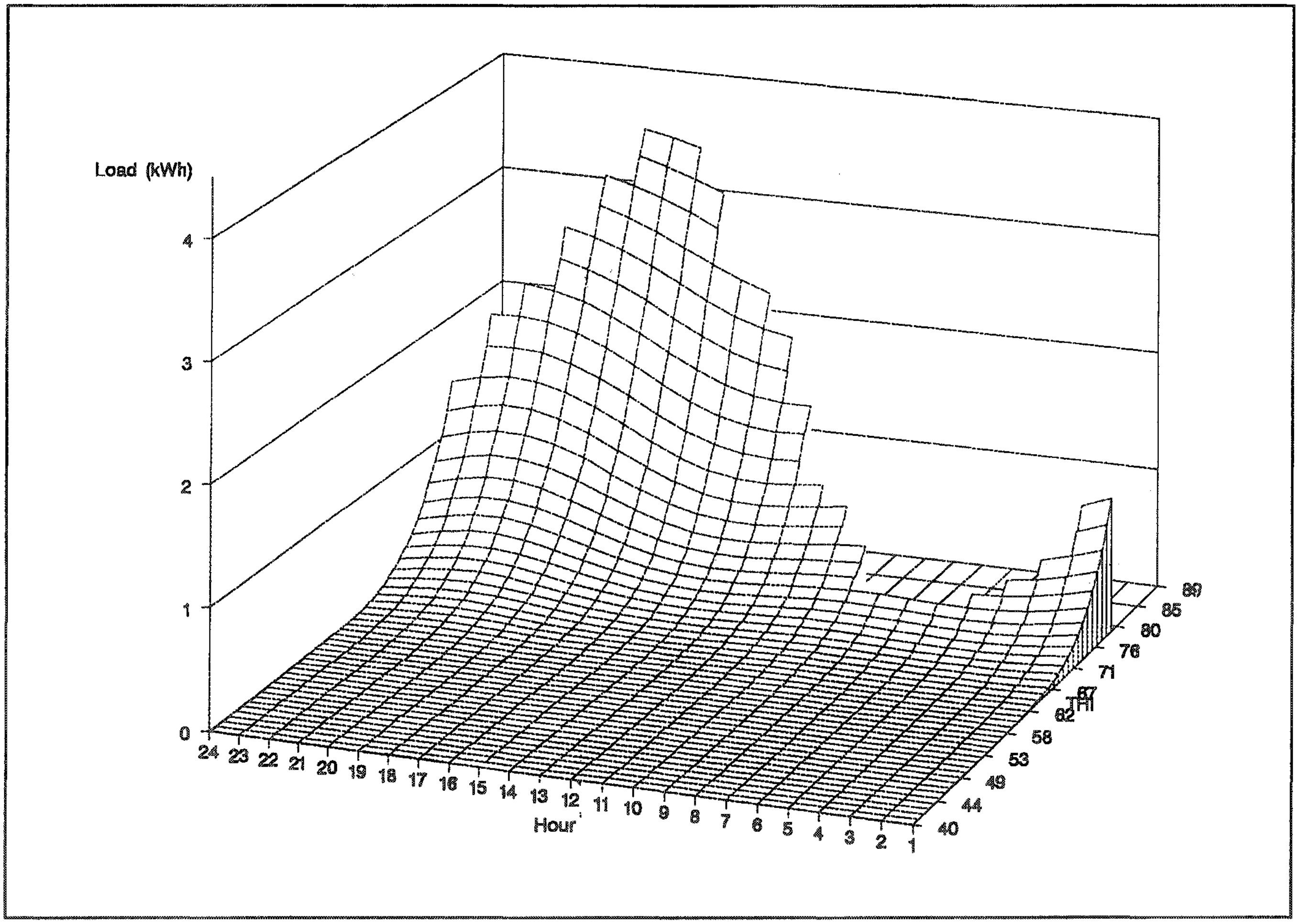

Figure 2. Smoothed Time-Temperature Matrix for Central Air Conditioning

and backcast 4 p.m. load (4 p.m. has been the typical peak system demand hour for PG&E in the recent past), and (4) the root mean squared error (RMSE) over the 24 hours of the paired load shapes. Figure 3 illustrates these measures for a sample comparison of load shapes. We summarized the measures over summer days and over the hottest five percent (in terms of THI-DD) of summer days to detect possible biases in the backcasting procedure and to indicate the level of backcast precision. Interpretation of these measures, with sample results from our analyses, are discussed in the Performance of Current Inputs section.

Issues in Input Development

We are interested in several issues of model input development: (1) evaluation of options for evaluating model performance, (2) how to aggregate metered data relative to possibly disparate (in terms of cooling load response) geographic regions, and over the days of the year, (3) the incremental value of additional metered data in improving model accuracy and precision, and (4) tailoring the model to focus on the aspects of the forecast which are of most interest[3].

Analysis

Performance of Current Inputs

We summarized the results of the backcast-to-sample comparisons, using the evaluation measures discussed in the Method of Evaluation section. The comparisons are based on daily pairs of load shapes: a normalized load shape derived from the all-regions all-days time-temperature matrix (the construction of which is described in the section on Developing a Time-Temperature Matrix) using historic weather for a given region, and the average sample load shape for that day across all metered residences in the region.

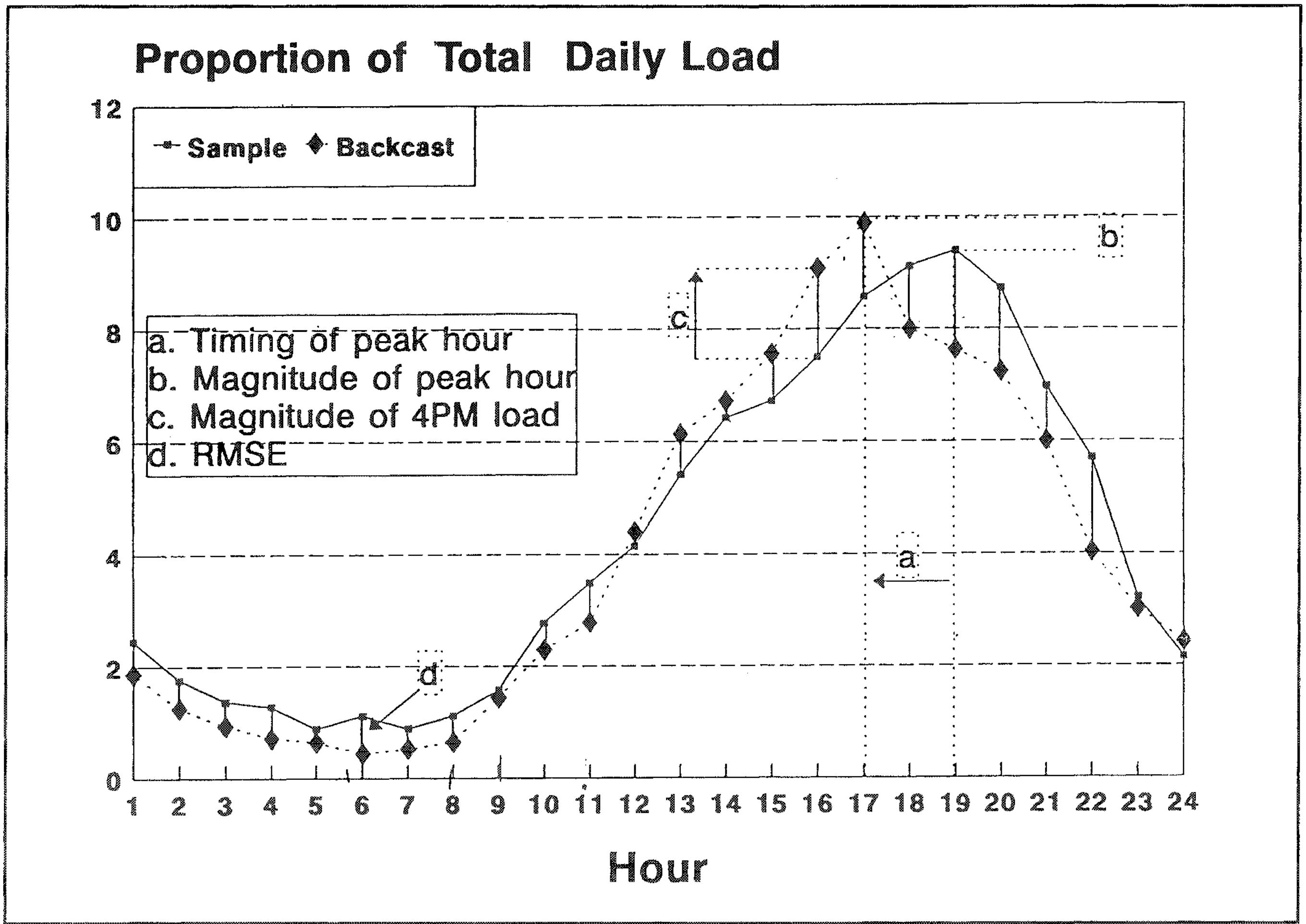

Figure 3. Measures Used for Load Shape Comparisons

Table 1 shows the results for CEC Region 2 (Sacramento weather station). The peak hour of the backcast load shape is the same as the peak hour of the sample load shape for 27% of the 920 summer days examined, and for 23% of the hottest five percentile of summer days. Peak load is predicted an average of 2.2% (of total daily load) too high for both the summer and the hottest days. The average prediction error ("mean absolute" in table) is 3.8% for summer days and 2.2% for the hottest days. The median difference between sample and backcast peaks is 1.7% for summer days and -2.0% for the hottest days. With regard to loads at the typical daily system peak hour (4 p.m.), the average summer load is overpredicted by 2.6%, while load on the hottest days is overpredicted by 1.4%. It is difficult to draw specific conclusions from the RMSE measure.

Region 4 peak load was overpredicted by an average of 1.6% for summer days and for the hottest days. Peak prediction is considerably better for Region 3 than for the other regions, with an average 1.0% overprediction for all summer days, and 0.4% overprediction for the hottest days. Prediction of 4 p.m. load is also better for Region 3 than for the other regions, with only an average of only 0.1% overprediction for Region 3's hottest days. In summary, the smoothed matrix tends to overpredict both peak and 4 p.m. sample loads.

These measures give a general indication of how well the time-temperature model fits the sample data, but must be interpreted with caution. First, the same data used to construct the time-temperature matrix were used to evaluate fit. This may lead to somewhat exaggerated descriptions of goodness of fit. Second, for a given set of weather conditions, the sample data shows considerable variation. The backcast load shape, which is based on long-term region-wide averages, cannot capture this variation, nor should it necessarily, since our ultimate objective is to predict system, not sample loads. In effect, we compare cell loads, which are based on long-term

Table 1. Summary of Measures Comparing Daily Backcast Load Shape to Sample for CEC Region 2

	Summer	Hottest 5%**
Timing of Peak Hour*		
% same	27	23
% 1 hour late	18	28
% 1 hour early	21	32
% > 2 hours off	20	4
Magnitude of Peak (sample-backcast)		
mean	-0.022	-0.022
mean absolute	0.038	0.022
median	0.017	-0.020
standard deviation	0.047	0.013
Magnitude of 4 p.m. Load (sample-backcast)		
mean	-0.026	-0.014
mean absolute	0.037	0.017
median	-0.021	-0.014
standard deviation	0.042	0.015
RMS		
mean	0.029	0.013
median	0.023	0.013
standard deviation	0.017	0.003
Number of day pairs	920	47

* backcast relative to sample
** in terms of THI-DD (see text)

system-wide averages, with single-date single-region averages (as moderated by loads for other hours of the day for the normalized load shape comparisons.) Our sample-to-backcast comparisons have been evaluated in relationship to this inherent variance, by considering overall performance rather than the performance for any single day[4]. To the extent that accurate forecasts for individual days (system peak days, for example) are of greater importance, different modeling procedures may be appropriate.

Data Aggregation over Regions and Days

The time-temperature matrix used for backcast comparisons in the previous section was developed using all central air conditioner data reported in the 1985-1989 AMP data sets. We found that the all-regions 1985-1989 time-temperature matrix performs reasonably well in "predicting" Region 3 sample loads from which the matrix was derived, but less well for Regions 2 and 4. It is likely that average air conditioning demand response to a given set of weather conditions (here as measured by THI on a given hour) varies according to geographic regions, and also by season, day type, and even from year to year. Thus, developing separate time-temperature matrices for relevant subsets of the sample data set could lead to better estimates of demand although at the expense of reduced sample size[5].

The aggregation issue for the time-temperature matrix may be viewed as one of balancing accuracy with precision: while in general more data is better than less, combining too much data may decrease accuracy, if the data combined are too disparate. The more disaggregated sample data become, however, the less data there are within a classification; consequently precision may be lowered. For example, a matrix based on only Region 2 central air conditioner data uses metered data from only

65 residences, while over 400 central air conditioners were metered between 1985-1989 in the AMP sample as a whole.

We used the statistical technique analysis of variance (ANOVA) to make these comparisons for a broader portion of the sample, and to judge the magnitude of the differences. Considering only hours with THI 68 or greater (by an assumption of the CEC model, hours that contribute to air conditioning loads), we modeled regional mean central air conditioner load for a selected hour of the day (once for 4 p.m., once for 6 p.m.) as a function of THI and the first-order factors region, season, day type, and two second-order factor terms: region crossed with season, and region crossed with day type. The season factor had two values, Spring (April and May) and Summer (June through October); data collected between November and March were excluded from these analyses. The day type factor had two values, Weekend and Weekday.

Results of the ANOVA indicate that, for a given level of THI, central air conditioner demand is about 0.35 kWh higher in the relatively mild Region 4 than in Region 2 and about 0.46 kWh higher than in the warmest region, Region 3. That residents respond to relative changes in THI is not surprising, although these effects might be at least in part due to the how representative weather at the weather station is of weather at the metered residences.) The coefficient estimates for seasonal effect suggest that for a given level of THI, central air conditioner demand is 0.185 higher in midsummer than in April and May. The ANOVA for 4 p.m. also indicated that region and season were important factors ($p <= 0.001$), and that day type was important as well ($p=0.004$). That day type is important at 4 p.m. seems reasonable, since residents are more likely to at home at 4 p.m. on weekends than at 4 p.m. on weekdays.

Since disaggregation by region seems justified, we computed separate time-temperature matrices for the three CEC Regions with the most metered data for central air conditioners: Region 2 (Sacramento weather station, 65 residences reporting metered central air conditioner data), Region 3 (Fresno weather station, 186 residences), and the relatively mild Region 4 (San Jose weather station, 133 residences).

We compared backcasts based on each region-specific matrix to backcasts based on the all-regions matrix, using the measures of backcast-to-sample similarity described above. Table 2 summarizes some results of the comparisons for CEC Region 2. This summary is based on days in the hottest five percentile of THI-DD between 1985 and 1989 at the Sacramento (CEC Region 2) NOAA station. Of course, the difficulty we noted earlier of using the same data to develop the matrix as to evaluate the matrix is even more pronounced when using a region-specific matrix to backcast load shapes for the same region, as we do here. The table shows that the Region 2 matrix results are noticeably different than the all-regions matrix results: Region 2 matrix backcasts are worse than all-regions matrix backcasts in predicting the timing of the peak hour (17% correct as opposed to 23% correct for the all-regions backcast), but do somewhat better in predicting the level of the peak, and achieve a lower mean RMSE. We also compared region-specific matrices to the all-regions matrix for CEC Regions 3 and 4. We found little difference between the performance of Region 3 and all-regions matrices, and that the Region 4 matrix did worse in timing but considerably better in the other three measures than the all-regions matrix. Region 3 data makes a relatively large contribution to the all regions matrix, since it has the hottest weather and the most central air conditioners metered.

In summary, the ANOVAs described above indicate that levels central air conditioner load at a given hour depend not only on THI but also on region, season, and sometimes day type, and our backcast comparisons suggest that this difference may be large enough to warrant using region-specific time-temperature matrices within CEC modeling framework. However we cannot quantify the forecasting improvement that may be achieved.

Value of Additional Years of Data

Another issue in collecting metered end-use load data is estimating the value of additional data, both in terms of increased sample size and in the length of the period over which metered data is collected. We begin to address the latter issue within the framework of the CEC model for residential air conditioning. In particular, we compared a time-temperature matrix developed from a single year (1988) of data alone to a matrix developed from four years of data (1985-1988) and compared backcasts from each of these two matrices to the sample data for 1989. Thus, sample data for testing the matrices were not used in the development of the matrices, although most of the central air conditioners metered in 1989 were also metered in earlier years (that is, the 1989 sample is not "independent" of the 1985-1988 sample.) While 1988 was a relatively hot year in the service territory, 1989 was relatively mild; this difference in weather may influence results.

We developed backcasts for 1989 from the 1988 and from the 1985-1988 time-temperature matrices. Table 3

Table 2. Summary of Backcast Performance of All-Regions and Region-Specific Matrix for CEC Region 2

Days in Top 5 Percent of THI-DD		
*Timing of Peak Hour**	*All Region Matrix*	*Region 2 Matrix*
% same	23	17
% 1 hour late	28	15
% 1 hour early	32	34
% > 2 hours off	4	8
Magnitude of Peak (sample-backcast)		
Normalized:		
mean	-0.022	-0.008
mean absolute	0.022	0.011
median	-0.020	-0.006
standard deviation	0.013	0.013
Magnitude of 4 p.m. Load (sample-backcast)		
Normalized:		
mean	-0.014	-0.016
mean absolute	0.017	0.018
median	-0.014	-0.016
standard deviation	0.015	0.014
RMSE		
Normalized:		
mean	0.013	0.010
median	0.013	0.010
standard deviation	0.003	0.003
Number of day pairs	47	47

* backcast relative to sample
** in terms of THI-DD (see text)

summarizes the results of the backcast-to-sample comparisons for Region 2, for days in the hottest ten percentile of THI-DD, respectively. For these hottest days, the 1988 matrix performs about as well as the 1985-1988 matrix, with the 1988 matrix slightly underestimating the level of the peak (by 0.3%) on average, and the 1985-1988 matrix slightly overestimating (by 0.6%) the level of the peak on average. Over all 1989 summer days, however, the 1985-1988 matrix estimates the peak level considerably better than does the 1988 matrix (an average 0.1% overestimation of the peak by the 1985-1988 matrix, as compared to an average 1.4% underestimation by the 1988 matrix.)

Our analyses do not provide a general test of the question "how well does a matrix developed from any one year of data perform as compared to a matrix developed from multiple years of data?", due to the possible influence of confounding factors (which could be present in any pair of matrices compared). Among these confounding factors are the possibility of temporal trends and possible differences in response to a given set of weather variables between mild years (1989) and hot years (1988). Even with such factors, studies similar to these analyses may be useful in determining when to stop metering.

Table 3. Summary of Backcast Performance of 1988 and 1985-1988 Matrices for CEC Region 2

1989 Summer Days in Top 10% of 1989 THI-DD	*1985-1988 Matrix*	*1988 Matrix*
*Timing of Peak Hour**		
% same	21	21
% 1 hour late	32	21
% 1 hour early	26	37
% > 2 hours off	0	0
Magnitude of Peak (sample-backcast)		
Normalized:		
mean	-0.003	0.006
mean absolute	0.018	0.018
median	-0.006	0.002
standard deviation	0.023	0.023
Magnitude of 4 p.m. Load (sample-backcast)		
Normalized:		
mean	-0.002	-0.002
mean absolute	0.018	0.017
median	-0.006	-0.005
standard deviation	0.022	0.021
RMSE		
Normalized:		
mean	0.013	0.014
median	0.012	0.012
standard deviation	0.004	0.005
Number of day pairs	19	19

* backcast relative to sample

In summary, the four-year matrix predicted the level of the Region 2 sample data load shape peak better than did the one-year matrix, and both matrices performed about equally well for the other measures. That more data works better than less, assuming uniform data quality, is not a surprising result. That the performance difference between the four-year and one-year matrix lies almost entirely in predicting peak level suggests specifying more precisely the items to be forecast, and the implication of that choice for accuracy in forecasting other items, should be examined. Finally, on the basis of these exploratory analyses, we do not have enough information to estimate the extent to which accuracy in forecasting system-wide residential cooling loads can be improved by additional years of data. For example, the degree to which additional data yields improved forecasts also depends on the method used to develop the smoothed load surface: a good smoothing algorithm might make up for a sparsely filled raw data matrix.

Focus of Forecasting

Another issue related to input aggregation is that of forecasting peak day versus average day loads. As we noted above, the CEC model has historically been used to forecast demand for the system peak day. One knows intuitively that peak demand is different in nature than average demand. Statistical theory reflects this intuition: peak loads are extreme values, which, as statistical entities, do not have the nice properties of other distributional parameters such as the mean and other moments.

These difficulties in forecasting peaks are compounded by other factors as well. For example, the definition of a peak depends on the measurement time interval and length of time period involved. The shorter the measurement time interval, the higher the peak, and the longer the period considered, the higher the peak. These and other issues arising in producing peak demand forecasts are discussed in detail in Limaye and Whitmore (1984).

Conclusions

We analyzed five years of hourly residential air conditioning data to develop new inputs for an end-use peak demand forecasting model. Our analyses provided insight in several issues including the appropriate level of disaggregation for the data, the usefulness of a weather normalization technique, and the incremental value of additional years of metered end-use data.

We found that inputs developed from data disaggregated by region, season, and to some extent day-type, lead to more accurate "backcasts" of observed data. However, we recognize that backcasting is a limited measure of the accuracy of our analyses. To some extent, our analyses also call into question the generalizability of the weather-normalization technique we employed. Our results on the value of additional years of sample data, while consistent with the expectation that more data lead to better results than less data, are not conclusive, because the evaluation methods are not comprehensive.

We believe there are significant challenges ahead for future efforts to use end-use metered data in developing forecasting model inputs. They range from more precise specification of the forecasting objective of the models (e.g, end-use peak, system coincident peak, load shape, minimum load conditions, etc.) and their relative priorities, to improved methods for generalizing results in order to predict loads for conditions unobserved in the data. Special effort should be devoted to better understanding the value of incremental (and expensive) end-use metering.

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Endnotes

1. The more sample data available to produce the raw time-temperature matrix, the less justified smoothing may be. In fact, for the backcast-to-sample summaries we use for matrix evaluation in this report, the raw matrix might be expected to perform better than the smoothed matrix. Alternative smoothing techniques, such as nonparametric smoothing, could also be considered.

2. The ultimate evaluation of the usefulness of the time-temperature matrix is in its performance as a component in estimation of systemwide residential class demand. We did not make this evaluation.

3. Other issues, not addressed in this report, include representation of weather (e.g., alternatives to the temperature-humidity index currently used in the model), and the scaling of the load shape derived from the time-temperature matrix from the normalized scale to energy units.

4. As an illustration of the variation over which the averaging to compute the time-temperature matrix has taken place, consider all days over the five year period in CEC Region 2 weather data THI 81 at 6 p.m. There were 44 such days. For these 44 days, average daily central air conditioner energy use in the region ranged from 0.65 kWh to 1.93 kWh, which represents nearly a three-fold variation in load for the identical (in terms of model inputs) conditions.

   To examine this variation from another perspective, we selected several days with similar THI profiles and compared the sample load shapes for these days. For example, we selected the 1986 system peak day (7/31/86, a Thursday), determined the hourly CEC Region 2 (Sacramento) THI profile for that day, and then examined historical weather data to find a second day with a similar load profile (9/5/86, a Friday) with THI profile from 3 p.m. to 9 p.m. identical to that recorded for 7/31/86. The sample load shapes have nearly identical peak load levels (2.87 kWh at 7 p.m. on 7/31/88, 2.84 kWh at 5 p.m. on 9/5/86), but on an energy-normalized basis, the two load shapes are dramatically different, with peak load hour accounting for over 14% of total daily load on 7/31/86 but only 10.5% of total daily load, and two hours earlier, for 9/5/86. We examined such matched pairs for each of the five system peak days, all of which showed notable differences, although somewhat less dramatically than the energy-normalized comparison described above.

5. Another advantage of computing matrices based on subsets of the data is that subset-specific matrices may be used for model cross-validation, so that the data used to evaluate model fit are different than those used to construct the time-temperature matrix. For example, one could test how well a time-temperature matrix based on Region 3 data works for predicting load shape characteristics of Region 2 sample data.

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